

Confidence Estimation in Structured Prediction

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Abstract

Structured classification tasks such as sequence labeling and dependency parsing have seen much interest by the Natural Language Processing and the machine learning communities. Several online learning algorithms were adapted for structured tasks such as Perceptron, Passive-Aggressive and the recently introduced Confidence-Weighted learning. These online algorithms are easy to implement, fast to train and yield state-of-the-art performance. However, unlike probabilistic models like Hidden Markov Model and Conditional random fields, these methods generate models that output merely a prediction with no additional information regarding confidence in the correctness of the output. In this work we fill the gap proposing few alternatives to compute the confidence in the output of non-probabilistic algorithms. We show how to compute confidence estimates in the prediction such that the confidence reflects the probability that the word is labeled correctly. We then show how to use our methods to detect mislabeled words, trade recall for precision and active learning. We evaluate our methods on four noun-phrase chunking and named entity recognition sequence labeling tasks, and on dependency parsing for 14 languages.

1 Introduction

Large scale natural language processing systems are often composed of few components each designed for solving a specific task. Example tasks are part-of-speech (POS) tagging (annotate words with their grammatical role), noun-phrase (NP) chunking (identify noun-phrases), information-extraction (IE) or

named-entity-recognition (NER) (identify entities such as persons, organizations, locations, amounts and dates) and dependency parsing (grammatical or semantical relations are identified between words of a sentence). In many cases the input of such systems is typed text, but in some cases it is the output of an automatic speech recognition component, or of an optical character recognition (OCR) layer that converts an image of printed text or hand writing to symbolic text.

Although the major tasks of algorithms designed to solve these problems is to make the right decision or prediction, often it is not enough as the output of one component is fed as input to a second one. The second component may act differently on inputs of various quality. Therefore it is desired in many situations to have not only an output, but to accompany it with a confidence estimation score, either for the entire prediction, or even per element (or word). For example, an interactive machine translation system can highlight low confidence translated segments for the user to inspect. Another example is an information-extraction algorithm that can use the confidence scores to detect low-confidence field candidates and apply a more restrictive or more aggressive extraction policy in order to allow the user for higher precision or higher recall.

The NLP applications mentioned above, among others, are also known as *structured prediction* tasks. The input is a general object, often with high-regularity, such sentences which are a *sequences* of words. The required output is also complex and structured, for example, the role of words in sentences are dependent and correlated. In the past decade structured prediction has gained increased interest by the machine learning community. After the introduction of conditional random fields (CRFs) (Lafferty, McCallum, and Pereira, 2001a), and maximum margin Markov networks (Taskar, Guestrin, and Koller, 2003), which are batch algorithms, new online methods were introduced. For example, the passive-aggressive algorithm (Crammer et al., 2006) originally designed for binary-classification, was adapted to NP chunking (Shimizu and Haas, 2006), dependency parsing (McDonald, Crammer, and Pereira, 2005b), learning preferences (Wick et al., 2009) and text segmentation (McDonald, Crammer, and Pereira, 2005a) and so on. These new online algorithms are fast to train and simple to implement, yet they generate models that output merely a prediction with no additional confidence information, as opposed to probabilistic models like CRFs or HMMs that naturally provide confidence estimation in the form of probability distribution over the outputs.

In this work we fill this gap proposing few methods to estimate confidence in the output of discriminative non-probabilistic algorithms. Some of our algorithms are very general and can be used in many structured prediction problems, and in combination of a wide-range of learning algorithms and models. We focus and exemplify our methods in two tasks: sequence labeling, and in particular named-entity recognition and noun-phrase chunking, and dependency parsing. In both tasks we show how to compute *per word* confidence estimates in the predicted label, such that the confidence reflects the probability that the label is correct.

Inspired by the recently introduced confidence-weighted learning (Dredze,

Crammer, and Pereira, 2008; Crammer, Kulesza, and Dredze, 2009) we develop methods that are based on its representation, and in particular we induce a distribution over labelings from the distribution maintained over weight-vectors. Additionally, we provide among the first results of applying CW algorithms to the tasks mentioned above.

After describing our proposed methods for confidence estimation, we provide comprehensive empirical results for evaluating various aspects of these algorithms. First, we evaluate the ability to estimate the confidence well in a relative setting where confidence is meaningful only when compared to another confidence quantity. Here, the goal of an algorithm is to rank all labeled words (in all sentences), that can be thought of as a retrieval of the erroneous predictions, which can then be passed to human annotator for an examination.

Second, some of the confidence measures are in the range $[0, 1]$ and thus can be thought of as probabilities. Our second set of experiments evaluates the accuracy of these confidence measures. The goal of the algorithm is that the frequency of correct inputs with some confidence value would be close to this confidence value. That is the predicted values between 0 and 1 would correspond their statistical properties over the data.

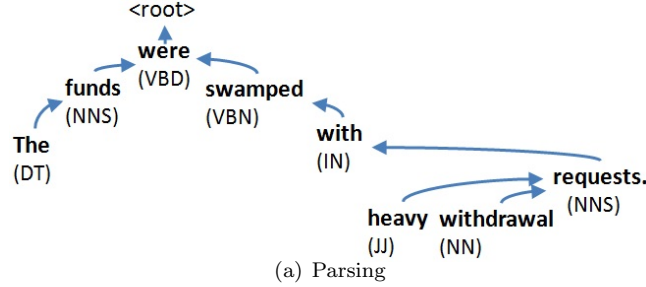
Next we describe two applications of using confidence. The first one is using the confidence to trade recall and precision, we show that our methods can be used to increase precision at cost of decreasing recall, where the overall f-measure is not dropping. The second application is active learning, where we use confidence to chose the sentences to be annotated.

A short version of this paper was presented in the conference on empirical methods in natural language processing (Mejer and Crammer, 2010). This long version contains the following *additional material* (1) Evaluation on a second task of dependency parsing of 14 languages. (2) Additional application of trading recall and precision. (3) Evaluation of additional algorithm, related to CRF (Lafferty, McCallum, and Pereira, 2001b). (4) Study of sensitivity to parameters in the main algorithm.

2 Structured Prediction

Structured prediction problems involve complex input and complex output, where both are composed of smaller atoms. Consider for example part-of-speech (POS) tagging. Given a sentence the goal is to annotate each word with a tag reflecting its grammatical role in the sentence. Here the input is a sentence composed of words and the output is a label of each word. Humans often perform this task by inspecting both the word identity and its context in the sentence.

Two additional related problems are Noun-Phrase (NP) chunking and Named Entity Recognition (NER). In both problems the input is a sentence as well, yet the goal is to annotate *segments* of words which are either noun-phrases or specific named entities. We model these problems in a similar way to POS, where the goal is to annotate each word whether it belongs to a noun-phrase (or a named-entity) or not.



Olympic	champion	Nathalie	Lancien	of	France	missed	the	attack
JJ	NN	NNP	NNP	IN	NNP	VBD	DT	NN
B-MISC	N	B-PER	I-PER	N	B-LOC	N	N	N

(b) Name Entity Recognition

Figure 1: Structured Prediction Examples (a) Dependency parsing: Connect words to a directed connected tree. (b) Name entity recognition: annotate words that are part of persons, locations and so on.

There are only two possible categories in NP chunking, one indicating that the word belongs to a noun-phrase and one indicating that it is not the case. NER is slightly more involved as typically there are several categories. For example a system developed about a decade ago (Tjong, Sang, and Meulder, 2003) uses four categories: Person, Location, Organization and Misc, yet additional categories are also used such as Date, Address, Amount and so on. As mentioned above the total number of categories is often larger by one to indicate that *none* of the possible named-entities is described by that word. A NER example is shown in Fig. 1 where the sentence and POS are given in the two top rows and the task is to find the proper labeling as shown in the bottom row.

Both of these problems are special case of the general problem of sequence labeling. Here given inputs $\mathbf{x} \in \mathcal{X}$ - e.g. sentences - with finite number n of atoms - e.g. words. The goal is to annotate each atom with a label $y \in Y$, where we assume that the number L of possible labels Y is finite and known. We denote by \mathbf{y} the concatenation of the labels of all atoms which belongs to the product of the label set, that is

$$\mathbf{y} \in \mathcal{Y}(\mathbf{x}) \text{ where } \mathcal{Y}(\mathbf{x}) = \overbrace{Y \times Y \dots Y}^n.$$

Dependency parsing of a sentence is one form of grammatical-reasoning of text. Given a sentence the goal is to output a directed-tree over the words, where an edge from one word to another indicate a dependency relation between the words. The output of dependency parsing is more complex than of shallow-parsing, in which the output is a sequence of grammatical roles per sentence, and is similar to the output defined by a context-free grammar. Concretely,

given a sentence $w_1 \dots w_n$ of length n the goal is to connect each word to some other word or a special word called *root*, that is the labels are the words of that input sentence or the *root*. In other words, all words depended exactly in some other words (called head), yet an head may have many dependents. Exactly one word must depend in the root, and all other words depend on it directly or indirectly. As our goal is to construct a parse *tree* over sentences there is one global constraint: the graph induced must be acyclic with no loops. That is, a word can not be dependent of another word, which in turn is a dependent of the first word, or a word the is a dependent of it (directly or indirectly). Formally a parse tree \mathbf{y} for a sentence with n words is a relation $\mathbf{y} \subset \{1 \dots n\} \times \{0 \dots n\}$, where the special index 0 indicates the root of the tree. For each word i the set $\{(i, t) \in \mathbf{y}\}$ is of size 1 (a function). The set $\{(i, 0) \in \mathbf{y}\}$ is of size 1, as only a single word is connected to the root. Finally, the induced graphs has no loops.

An illustration of a dependency parse is shown in Fig. 1 .

We use a unified notation for both sequential labeling and dependency parsing (as well as other problems) and define a scoring function $s(\mathbf{x}, \mathbf{z})$, which assign a real scalar value scoring how well the complex label \mathbf{y} should be the label of the input \mathbf{x} . Given such a function a prediction is defined to be the labeling with maximal score, that is,

$$\hat{\mathbf{y}} = \arg \max_{\mathbf{z} \in \mathcal{Y}(\mathbf{x})} s(\mathbf{x}, \mathbf{z}), \quad (1)$$

where $\mathcal{Y}(\mathbf{x})$ are all possible labelings of the input \mathbf{x} , e.g. all possible parse trees for a given sentence \mathbf{x} .

In this work, we restrict ourself to linear functions $s(\cdot, \cdot)$ of some parameters (Collins, 2002; Crammer, Dredze, and Kulesza, 2009), that is,

$$s(\mathbf{x}, \mathbf{z}) = \boldsymbol{\mu} \cdot \boldsymbol{\Phi}(\mathbf{x}, \mathbf{z}) , \quad (2)$$

where $\boldsymbol{\Phi}(\mathbf{x}, \mathbf{y}) \in \mathbb{R}^d$ is a joint feature mapping of an instance \mathbf{x} and a labeling \mathbf{y} into a common vector space. Features are derived from combinations of words (unigrams or n-grams), part-of-speech, orthographic features such as capital letters, hyphens and so on. The vector $\boldsymbol{\mu} \in \mathbb{R}^d$ parameterize the function $s(\cdot, \cdot)$, where $\boldsymbol{\mu}$ is chosen by a learning algorithm such that for all sentences in the training set, the label $\hat{\mathbf{y}}$ output by the system is close or similar to the correct label (or gold label) of these sentences, that is

$$\hat{\mathbf{y}} = \arg \max_{\mathbf{z} \in \mathcal{Y}(\mathbf{x})} \boldsymbol{\mu} \cdot \boldsymbol{\Phi}(\mathbf{x}, \mathbf{z}) \quad (3)$$

should be close to the best label.

A brute-force approach for computing the best label $\hat{\mathbf{y}} = \arg \max_{\mathbf{z} \in \mathcal{Y}(\mathbf{x})} \boldsymbol{\mu} \cdot \boldsymbol{\Phi}(\mathbf{x}, \mathbf{z})$ is not feasible as, typically, the size of the set $\mathcal{Y}(\mathbf{x})$ grows very fast with the size n of the input \mathbf{x} . For example, in sequence labeling there are L^n possible labeling of a sentence of length n , and there are n^{n-2} directed acyclic trees over n words (or nodes).

Input	Mr.	Smith	founder	of	Smith	Inc.	Score
Output	Per	Per	N	N	Org	Org	17.8
Best Alt'	Per	Per	Per	N	Org	Org	16.4
			1.4				

Input	Mr.	Smith	founder	of	Smith	Inc.	Score
Output	Per	Per	N	N	Org	Org	17.8
Best Alt'	Per	Per	N	Misc	Misc	Misc	12.2
				5.6			

Figure 2: Illustration of the margin based method to estimate confidence. Score difference between the highest and second highest scoring label per word is defined as the confidence. In this example the word "of" is labeled with higher confidence than the word "founder".

We thus employ common approach and factor the scoring function $s(\mathbf{x}, \mathbf{y})$ by factoring the appropriate feature function $\Phi(\mathbf{x}, \mathbf{y})$. For sequence labeling we allow only functions over a single label or pairs of consecutive labels,

$$\Phi(\mathbf{x}, \mathbf{y}) = \sum_{p=1}^n \Phi(\mathbf{x}, y_p) + \sum_{q=2}^n \Phi(\mathbf{x}, y_q, y_{q-1}) . \quad (4)$$

Such factorization allows to perform the search for the best labeling $\hat{\mathbf{y}}$ time linear in n and quadratic in L using the Viterbi dynamic-programming algorithm.

For dependency parsing we build on MSTParser of McDonald et al. (2005) and focus on non-projective parsing (tree edges may cross) with non-typed (un-labeled) edges. MSTParser factors the score for each parse to be a sum of the score over its edges, that is,

$$\Phi(\mathbf{x}, \mathbf{y}) = \sum_{(i,j) \in \mathbf{y}} \Phi(\mathbf{x}, i, j) ,$$

where as mentioned above every pair $(i, j) \in \mathbf{y}$ represents a single edge between word w_i and word w_j . Example features are the distance between the two words, words identity and words part-of-speech. Using this factorization, the search for the best tree can be computed efficiently by first constructing a full directed graph over the words of the sentence with weighted edges and then outputting the maximal spanning tree (MST) of the graph, which can be computed for dense graphs in quadratic time in the length of the sentence using Chu-Liu-Edmonds (CLE) algorithm (Chu and Liu, 1965; Edmonds, J., 1967; Tarjan, R. E., 1977).

3 Confidence Estimation

Many large-margin-based training algorithms maintain and output linear models in the form of Eq. (3). Linear models are easy to train, yet in the end-of-

	Margin Based	Marginal Probability	K -Best Alternatives	K -Alternatives by Stochastic Models
<i>Absolute</i> confidence score	No (only relative)	Yes	Yes	Yes
Hyper-parameters tuning	No	Yes	Yes	Yes
Complexity Sequences	$O(n \cdot \mathcal{Y} ^2)$	$O(n \cdot \mathcal{Y} ^2)$	$O(K \cdot n \cdot \mathcal{Y} ^2)$	$O(K \cdot n \cdot \mathcal{Y} ^2)$
Complexity Parsing	$O(n^3)$	-	$O(K \cdot n^2)$	$O(K \cdot n^2)$

Table 1: Properties of confidence estimation methods.

the-day such models are designed merely to make a prediction which is a single labeling $\hat{\mathbf{y}}$ given an input \mathbf{x} , with no additional information about the quality or correctness of that prediction. This behavior assumes that the predicted labeling $\hat{\mathbf{y}}$ will be used ignoring the quality of each specific output (as opposed to global quality of the system, such as average accuracy, precision or recall).

There are situations for which additional information per labeling $\hat{\mathbf{y}}$ is useful, for example when the user of the prediction system has the option to ignore $\hat{\mathbf{y}}$, or when using erroneous $\hat{\mathbf{y}}$ is worse than not using it at all. One possible scenario is when the output $\hat{\mathbf{y}}$ is used as an input of another system that integrates various input sources or is sensitive to the correctness of the specific prediction. In such cases, additional confidence information about the correctness of these feeds for specific input can be used to improve the total output quality. For example, data mining systems use NER predictors as sub-components. Such systems may use few NER predictors which all provide *confidence* information about their output, and allow the data-mining system to integrate better the output from all NER predictors, and overcome possible mistakes.

Another case where confidence information is useful, is when there is an additional agent that validates the output $\hat{\mathbf{y}}$ (as was done in building RCV1 (Lewis et al., 2004)). Confidence information associated with output $\hat{\mathbf{y}}$ can be used to direct the agent to small subset of “suspect” outputs rather than use a random sample or evaluate all outputs.

We now describe three methods to compute confidence in prediction of the form of a single number per prediction. One method only provide *relative* confidence information. This numeric information can be only used to compare two outputs and decide which is of better quality. One use of such relative confidence information is to *rank* all predictions or outputs according to their confidence numeric-score, and validate the output of the outputs which are assigned with the most low-confident score values. One property of this *relative* score is that any monotonic transformation of the confidence values yields equivalent confi-

dence information (and ranking).

Other two methods described below provide *absolute* numeric confidence information in the prediction. Conceptually, the numeric confidence information is given as the probability of a prediction to be correct. We interpret these probabilistic outputs in a frequentists approach. A large set of events (predictions) all assigned with similar probability confidence value ν of being correct, indeed should contain about ν fraction of the predictions of that group correct. Clearly, any absolute information is relative as well, as two absolute confidence values may also be compared to each other to determine which output is of better quality.

In Sec. 3.1 we describe our relative confidence method which is based on extending the notion of *margin* originally used to design support-vector machines in the context of binary-classification (Boser, Guyon, and Vapnik, 1992; Bartlett et al., 2000). Intuitively, we define the confidence in a prediction to be the difference between the score of the (best) labeling $s(\mathbf{x}, \hat{\mathbf{y}})$, and an additional prediction.

Next, in Sec. 3.2 we define a probability distribution by using the score values $s(\mathbf{x}, \mathbf{z})$ as arguments of a suitable-function yielding non-negative values which sum to unit, and then compute the marginals induced from this distribution. Such method is used for example in conditional-random fields (CRF) (Lafferty, McCallum, and Pereira, 2001b).

Finally, our third approach, which output absolute confidence information as well, is described in Sec. 3.3. This method generates few alternative outputs additional to $\hat{\mathbf{y}}$, and evaluates the confidence by computing the agreement between the output $\hat{\mathbf{y}}$ and the alternatives. We use two methods to generate the alternatives: one deterministic based on extension of the prediction algorithms to produce K -best predictions, and one stochastic based on sampling models. A comparison of the confidence estimation methods properties is summarized in Table 1, each row is described in details in the appropriate place below.

3.1 A Margin-Based Method

Our first method extends the notion of margin known mainly in the context of support vector machines (Bartlett et al., 2000). Originally, margin is a geometrical concept and is defined to be the distance of an input point embedded in some vector space to the separating hyperplane. Later (e.g. (Bredensteiner and Bennet, 1999; Crammer and Singer, 2001; Har-Peled, Roth, and Zimak, 2002; Weston and Watkins, 1999; Taskar, Guestrin, and Koller, 2003)) it was extended in the context of multiclass problems. For example, in sequential labeling it is defined to be the difference between the best scoring labeling $\hat{\mathbf{y}}$ and the second best,

$$\boldsymbol{\mu} \cdot \boldsymbol{\Phi}(\mathbf{x}, \hat{\mathbf{y}}) - \max_{\mathbf{z} \neq \hat{\mathbf{y}}} \boldsymbol{\mu} \cdot \boldsymbol{\Phi}(\mathbf{x}, \mathbf{z}) .$$

This definition is too crude for our purpose as we need a measure of confidence per unit, or word in our tasks. Thus, we refine the above definition and define the margin of the p th word to be the difference in the score of the best labeling

Input	Mr.	Smith	founder	of	Smith	Inc.
Output	<i>Per</i>	<i>Per</i>	<i>N</i>	<i>N</i>	<i>Org</i>	<i>Org</i>
None	0.82	0.93
Per	0.10	0.02
Loc	0.03	0.01
Org	0.04	0.01
Misc	0.01	0.03
			1.0	1.0		

Figure 3: Illustration of the marginal-probability based method to estimate confidence. The confidence in the chosen label is defined to be the marginal-probability of the label. In this example the word "of" is labeled as *None* with higher confidence than the word "founder".

score and the score of the best labeling where we set the label of that word to anything but the label with the highest score. Formally, as before we define the best labeling $\hat{\mathbf{y}} = \arg \max_{\mathbf{z}} \boldsymbol{\mu} \cdot \boldsymbol{\Phi}(\mathbf{x}, \mathbf{z})$, then the margin of the p th word is defined to be,

$$\delta_p = \boldsymbol{\mu} \cdot \boldsymbol{\Phi}(\mathbf{x}, \hat{\mathbf{y}}) - \max_{\mathbf{z}_{|p} \neq \hat{\mathbf{y}}_{|p}} \boldsymbol{\mu} \cdot \boldsymbol{\Phi}(\mathbf{x}, \mathbf{z}) , \quad (5)$$

where $\mathbf{z}_{|p}$ is the labeling of the p th word according to the labeling \mathbf{z} of the entire input. Since labeling of consecutive words are dependent according to the model the labeling of additional words may change from $\hat{\mathbf{y}}$ by the restriction that the labeling of the p th word is not its labeling according to the best labeling $\hat{\mathbf{y}}_p$. In parsing, for example, changing the parent of a single word in a parse tree may cause a loop in the graph that require changing the parents of additional words to resolve the loop.

We refer to this method as **Delta** where the confidence information is the margin which is a difference or delta between two score values. Clearly, the absolute margin value δ_p provides confidence score that is only relative and not absolute, namely it can be used to compare the confidence in two labeling, yet there is no semantics defined over the scores as it is not calibrated to be in $[0, 1]$.

An illustration of the margin method is given in Fig. 2 for the sentence fragment *Mr Smith founder of Smith Inc..* The top row of both panels shows the highest scoring labeling $\hat{\mathbf{y}}$ which attains a score of 17.8 in our case. The second row of each panel shows the best labeling where the label of some word is restricted. The top panel shows the best labeling where the label of the word *founder* is restricted not to be *N* - its labeling according to $\hat{\mathbf{y}}$. Clearly its score of 16.4 is not higher than the score of the best labeling, as the max operator is performed over a strict subset of possible labelings \mathbf{z} . The bottom panel shows similar process for the word *of* where its labeling is restricted from being *N*, and the one that has the highest score is *Misc*, the difference in score is 5.6 which is defined to be the confidence value. Thus, in our example, the confidence in the

labeling of the word *of* is higher than the confidence in the labeling of the word *founder*.

A straightforward implementation of the **Delta** method requires repeating the inference process n times, once per word of the input, each time with a single constraint over the labeling, that is, the label \hat{y}_p is not allowed for the p th word - the word for which the confidence is being evaluated. Such implementation costs $O(n \cdot (\text{inference cost}))$. We used this approach for dependency parsing task, and thus the computation complexity is $O(n \cdot n^2)$ which is cubic in n .

For the sequence labeling task the computation of **Delta** confidence can be improved by using the forward-backward-Viterbi algorithm (similar to standard forward-backward algorithm (Rabiner, 1989)). This dynamic programming algorithm allows to efficiently compute the score of the best sequence labeling that includes a specific label constraint, therefore the computation of the **Delta** confidence scores can be performed in $O(n \cdot |\mathcal{Y}|^2)$, the same complexity as the standard Viterbi algorithm used for sequence labeling prediction.

3.2 Marginal-Probability Method

The second method we describe is based on specific function converting score values into probabilities. We follow the same modeling of conditional random fields (CRF) (Lafferty, McCallum, and Pereira, 2001b) and define the conditional probability,

$$P(\mathbf{y}|\mathbf{x}) = \frac{\exp \{c(\boldsymbol{\mu} \cdot \boldsymbol{\Phi}(\mathbf{x}, \mathbf{y}))\}}{Z_{\mathbf{x}}} \quad (6)$$

where $Z_{\mathbf{x}}$ is a normalization factor over all possible labeling to the input \mathbf{x} ,

$$Z_{\mathbf{x}} = \sum_{\mathbf{z} \in \mathcal{Y}(\mathbf{x})} \exp \{c(\boldsymbol{\mu} \cdot \boldsymbol{\Phi}(\mathbf{x}, \mathbf{z}))\}, \quad (7)$$

and $c > 0$ is a scaling parameter. While in some learning algorithms, such as CRFs, the model parameters are trained to maximize the log-likelihood of data using the above conditional probability, this is not the case for other algorithms such as ones that are based on large-margin such as the passive-aggressive (Crammer et al., 2006) algorithm or the confidence-weighted algorithm (Dredze, Crammer, and Pereira, 2008; Crammer, Dredze, and Pereira, 2008), both described below. For this reason the coefficient c is used to allow tuning of the model score to confidence score.

We define the confidence in a prediction of the p th word to be the marginal probability of that prediction, that is,

$$P(\hat{\mathbf{y}}_{|p}|\mathbf{x}) = \sum_{\mathbf{z} : \mathbf{z}_{|p} = \hat{\mathbf{y}}_{|p}} P(\mathbf{z}|\mathbf{x}).$$

Using the dynamic-programming forward-backward algorithm (Rabiner, 1989) for sequence labeling the marginal probability can be efficiently computed in $O(n \cdot |\mathcal{Y}|^2)$ for all assigned labels $P(\hat{\mathbf{y}}_{|p}|\mathbf{x})$ and $p = 1 \dots n$. It is common to

Input	Mr.	Smith	founder	of	Smith	Inc.
Output	<i>Per</i>	<i>Per</i>	<i>N</i>	<i>N</i>	<i>Org</i>	<i>Org</i>
Alt #1	<i>Per</i>	<i>N</i>	<i>N</i>	<i>N</i>	<i>Org</i>	<i>Org</i>
Alt #2	<i>Per</i>	<i>Per</i>	<i>Per</i>	<i>N</i>	<i>Org</i>	<i>Org</i>
Alt #3	<i>Per</i>	<i>Per</i>	<i>N</i>	<i>N</i>	<i>Org</i>	<i>Org</i>
Alt #4	<i>Misc</i>	<i>Misc</i>	<i>Misc</i>	<i>N</i>	<i>Per</i>	<i>N</i>
Alt #5	<i>Per</i>	<i>Per</i>	<i>N</i>	<i>N</i>	<i>N</i>	<i>Org</i>
Score	4/5	3/5	3/5	5/5	3/5	4/5

Figure 4: Illustration of the alternatives method to estimate confidence. Confidence is defined as the fraction of alternative labeling that agree with the prediction.

refer to the quantities computed by the forward-backward algorithm by γ , so we also refer to this method as **Gamma**. We report the results of this method only in the context of sequence labeling and not dependency parsing, as we found empirically that it was shown not to perform well compared to **Delta** described above and some of the methods we describe next.

An illustration of this process appear in Fig. 3 where the best labeling appears in the top row, and the marginals for two words appear in the following rows. In this example the confidence in the prediction of the word *founder* is defined to be 0.82 and the confidence in the prediction for the word *of* is defined to be 0.93, the marginal value in both cases. One notable property is that the confidence values are close to 1, this is because of the exponent-function used to convert scores to probabilities, a phenomena that was shown to appear in other contexts (Malkin and Bilmes, 2009).

3.3 Confidence by Alternatives

This method works in two stages. First, a set of K alternative labeling for a given input sentence are generated, where the predicted labeling $\hat{\mathbf{y}}$ is not necessarily one of the k labeling. Then, the confidence in the predicted labeling is computed by evaluating the agreement (or disagreement) between $\hat{\mathbf{y}}$ and the K alternatives. In other words, the confidence in the prediction for a specific word is defined to be the proportion of labeling which are consistent with the predicted label. Formally, let $\mathbf{z}^{(i)}$ for $i = 1 \dots K$ be the K labeling for some input \mathbf{x} , and let $\hat{\mathbf{y}}$ be the actual prediction for the input. (We do not assume that $\hat{\mathbf{y}} = \mathbf{z}^{(i)}$ for some i). The confidence in the label \hat{y}_p of word $p = 1 \dots |\mathbf{x}|$ is defined to be

$$\nu_p = \frac{\left| \left\{ i : \hat{y}_p = z_p^{(i)} \right\} \right|}{K}. \quad (8)$$

The process is illustrated in Fig. 4. The input is given in the top row and the prediction is given in the next row. The example output $\hat{\mathbf{y}}$ includes a person

name *Mr Smith* and a company name *Smith Inc.* In the next five rows there are five alternative labelings to the input sentence. Numeric confidence scores are given in the bottom line, and are the fraction of alternatives which agree with the labeling of the output. For example, in the alternative just after the output only the word *Mr* is part of the person name while the following word *Smith* is labeled as a none entity. The confidence for the word *founder* is $0.6 = 3/5$ as in three alternatives out of five the labeling of it (*None*) agrees with the labeling of the output. The confidence for the word *of* is $1.0 = 5/5$ as all alternatives agree with the labeling of the output (*None*).

We tried two major approaches to generate K possible alternatives: deterministic and stochastic.

3.3.1 K -Best Predictions

The inference procedures are returning the labeling $\hat{\mathbf{y}}$ that achieves the highest score in Eq. (1), $\hat{\mathbf{y}} = \arg \max_{\mathbf{z} \in \mathcal{Y}(\mathbf{x})} s(\mathbf{x}, \mathbf{z})$. We modify the inference algorithm to return not a single labeling but the best K distinct labelings with highest score. Formally, we pick the top- K *distinct* labelings that satisfy,

$$s(\mathbf{x}, \mathbf{z}^{(1)}) \geq s(\mathbf{x}, \mathbf{z}^{(2)}) \geq \dots \geq s(\mathbf{x}, \mathbf{z}^{(K)}) \geq s(\mathbf{x}, \mathbf{z}),$$

$$\text{for all } \mathbf{z} \notin Z = \{\mathbf{z}^{(1)}, \dots, \mathbf{z}^{(K)}\}.$$

By definition we have that the first labeling is the predicted output $\mathbf{z}^{(1)} = \hat{\mathbf{y}}$ and that all K labelings differ from each other $\mathbf{z}^{(i)} \neq \mathbf{z}^{(j)}$ for $i \neq j$. Specifically, we use the k-best Viterbi algorithm (Chow and Schwartz, 1989) to find the k-best sequence labeling in $O(K \cdot n \cdot |\mathcal{Y}|^2)$, and for dependency parsing we used the k-best Maximum Spanning Trees algorithm (Hall, 2007; Camerini, Fratta, and Maffioli, 1980) to produce the K parse trees with the highest score in $O(K \cdot n^2)$.

We use two variants of this approach. The first variant assigns uniform importance to each of the K labelings ignoring the actual score values. We call this method KB, for K -best. The second variant assigns a specific importance weight ω_i to each labeling $\mathbf{z}^{(i)}$, and evaluate confidence using the weights, where we set the weights to be their score value clipped at zero from below $\omega_i = \max\{0, \mu \cdot \Phi(\mathbf{x}, \mathbf{z}^{(i)})\}$. (In practice, top scores were always positive.) We call this method WKB for weighted K -best. Eq. (8) is naturally extended to a weighted set,

$$\nu_p = \frac{\sum_{i : \hat{\mathbf{y}}_p = \mathbf{z}_p^{(i)}} \omega_i}{\sum_i \omega_i} . \quad (9)$$

3.3.2 Stochastic Models

Previous method used a single model to generate few alternatives. This approach is complimentary, we use a single model to generate (stochastically) few

additional models, each is used to generate a single alternative (best according to itself) labeling. Concretely, given a model μ learned by some algorithm we induce a probability distribution over weight-vectors given μ , denoted by $\Pr[\mathbf{w}|\mu]$. We then draw a set of K weight-vectors $\mathbf{w}_i \sim \Pr[\mathbf{w}|\mu]$, and use each to output a best labeling according to it to get a set of alternatives,

$$Z = \{\mathbf{z}^{(i)} : \mathbf{z}^{(i)} = \arg \max_{\mathbf{z}} \mathbf{w}_i \cdot \Phi(\mathbf{x}, \mathbf{z}) \text{ where } \mathbf{w}_i \sim \Pr[\mathbf{w}|\mu]\} . \quad (10)$$

Again we use two variants of this approach. The first variant is more generic we define the probability distribution over weights to be Gaussian with an isotropic covariance matrix, $\Sigma = sI$ for some positive scale information s , that is we have that, $\mathbf{w} \sim \mathcal{N}(\mu, \Sigma)$, where μ are the parameters returned by the learning algorithm. The value of s was tuned on the training set. We denote this method **KD-Fix** for K -draws with fixed standard deviation. This method is especially appealing, since it can be used in combination with training algorithms that do *not* maintain confidence information, such as the Perceptron or PA.

The second variant is used with classifiers that not only maintain a single weight vector μ but also a distribution weight vectors. For example, the confidence weighted classifier (CW) described below in Sec. 4 maintains by definition a Gaussian distribution over weights, $\mathbf{w} \sim \mathcal{N}(\mu, \Sigma)$. We proceed as the previous variant, given an input the algorithm draws K alternative weight vectors according to the distribution maintained by CW scaled by scalar s , that is $s\Sigma$, and output the best labeling with respect to each weight vector. Again the value of s was tuned on the training set. We denote this method **KD-PC** for K -draws by parameter confidence.

We stress that the two variants generating the set of K alternatives are inherently different from each other. The first deterministic approach generates few labelings from the same model, all of the labelings are different from each other, and one of them is always the prediction $\hat{\mathbf{y}}$. Additionally, although different from each other the labelings are close (or similar) to each other (in term of Hamming difference), as all attain very close (to the best) score values, because the score over sequences decompose to scores over words and pairs of adjacent words. The second stochastic approach generates one alternative per sampled model. With high probability these models differ from the model μ used to make the prediction, and thus the output labeling $\hat{\mathbf{y}}$ may be different from each of the alternatives. However, if the covariance matrix is close to zero, the sampled weight-vectors are likely to be close (in terms of Euclidean distance) to μ and thus produce similar labeling to $\hat{\mathbf{y}}$, that is, there may be overlap between alternative labeling.

Using the stochastic models approach the K alternative predictions are generated by executing the inference algorithm K times, each time with different sampled model, therefore the computing complexity is $O(K \cdot (\text{inference cost}))$, that is $O(K \cdot n^2)$ for parsing and $O(K \cdot n \cdot |\mathcal{Y}|^2)$ for sequence labeling.

4 Learning

The algorithms described above to compute confidence are designed for linear models decomposed over units, and work with any algorithm in such setting. We evaluate the confidence estimation methods described in Sec. 3 using online learning algorithms (Cesa-Bianchi and Lugosi, 2006). These algorithms are fast, efficient, simple to implement and work well in practice. The passive-aggressive (PA) algorithms (Crammer et al., 2006) were shown to achieve state-of-the-art performance in many tasks such as NP chunking (Shimizu and Haas, 2006), dependency parsing (McDonald, Crammer, and Pereira, 2005b), learning preferences (Wick et al., 2009) and text segmentation (McDonald, Crammer, and Pereira, 2005a). Recently, confidence weighted (CW) algorithms were introduced for binary classification (Dredze, Crammer, and Pereira, 2008; Crammer, Dredze, and Pereira, 2008) and multi-class problems (Crammer, Dredze, and Kulesza, 2009) and were shown to outperform many competitors. We next describe both PA and CW algorithms for structured prediction. Both versions are reductions from structured problems to binary classification in a manner similar to the reduction performed for parsing using the Perceptron algorithm (Collins, 2002).

Online algorithms work in rounds. On the i th round the online algorithm receives an input $\mathbf{x}_i \in \mathcal{X}$ and applies its current rule to make a prediction $\hat{\mathbf{y}}_i \in \mathcal{Y}(\mathbf{x}_i)$, it then receives the correct label $\mathbf{y}_i \in \mathcal{Y}(\mathbf{x}_i)$ and suffers a loss $\ell(\mathbf{y}_i, \hat{\mathbf{y}}_i)$. At this point, the algorithm updates its prediction rule with the pair $(\mathbf{x}_i, \mathbf{y}_i)$ and proceeds to the next round. A summary of online algorithms can be found in the book written by Cesa-Bianchi and Lugosi (2006). As noted above, in structured prediction we assume a joint feature representation, $s(\mathbf{x}, \mathbf{z}) = \boldsymbol{\mu} \cdot \Phi(\mathbf{x}, \mathbf{z})$ for $\Phi(\mathbf{x}, \mathbf{y}) \in \mathbb{R}^d$ (see Eq. (2) and the text after it).

Passive-Aggressive Learning We first review a version of the passive-aggressive (PA) algorithms for structured prediction (Crammer et al., 2006, Sec. 10). The algorithm maintains a weight vector $\boldsymbol{\mu}_i \in \mathbb{R}^d$ and updates it on each round using the current input \mathbf{x}_i and label \mathbf{y}_i , by optimizing:

$$\begin{aligned} \boldsymbol{\mu}_{i+1} = \arg \min_{\boldsymbol{\mu}} \quad & \frac{1}{2} \|\boldsymbol{\mu} - \boldsymbol{\mu}_i\|^2 + C\xi \\ \text{s.t.} \quad & \boldsymbol{\mu} \cdot \Phi(\mathbf{x}_i, \mathbf{y}_i) - \boldsymbol{\mu} \cdot \Phi(\mathbf{x}_i, \hat{\mathbf{y}}_i) \geq \ell(\mathbf{y}_i, \hat{\mathbf{y}}_i) - \xi \quad , \quad \xi \geq 0 \quad , \end{aligned} \quad (11)$$

where the loss $\ell(\mathbf{y}_i, \hat{\mathbf{y}}_i)$ is taken as the Hamming distance between the two labeling which is number of incorrect edges in the parse tree or incorrect labels in the sequence labeling tasks, and $C > 0$ controls the tradeoff between optimizing the current loss and being close to the old weight vector. To solve Eq. (11) we define the difference between the feature vector associated with the true labeling \mathbf{y}_i and the feature vector associated with some labeling \mathbf{z} to be, $\Delta_{i,\mathbf{y},\mathbf{z}} = \Phi(\mathbf{x}_i, \mathbf{y}_i) - \Phi(\mathbf{x}_i, \mathbf{z})$, and in particular, when we use the current model's prediction $\hat{\mathbf{y}}_i$ we get,

$$\Delta_{i,\mathbf{y},\hat{\mathbf{y}}} = \Phi(\mathbf{x}_i, \mathbf{y}_i) - \Phi(\mathbf{x}_i, \hat{\mathbf{y}}_i) \quad .$$

Algorithm 1 Sequence Labeling PA

Input:

- Joint feature mapping $\Phi(\mathbf{x}, \mathbf{y}) \in \mathbb{R}^d$
- Tradeoff parameter C

Initialize:

- $\boldsymbol{\mu}_0 = \mathbf{0}$

For $i = 1, 2, \dots, T$

- Get input $\mathbf{x}_i \in \mathcal{X}$
- Predict best labeling $\hat{\mathbf{y}}_i = \arg \max_z \boldsymbol{\mu}_{i-1} \cdot \Phi(\mathbf{x}_i, \mathbf{z})$
- Get correct labeling $\mathbf{y}_i \in \mathcal{Y}(\mathbf{x}_i)$
- Define $\Delta_{i,\mathbf{y},\hat{\mathbf{y}}} = \Phi(\mathbf{x}, \mathbf{y}_i) - \Phi(\mathbf{x}, \hat{\mathbf{y}}_i)$
- Compute (from Eq. (12))

$$\alpha_i = \min \left\{ C, \frac{\max \{0, \ell(y_i, \hat{y}_i) - \boldsymbol{\mu}_i \cdot \Delta_{i,\mathbf{y},\hat{\mathbf{y}}}\}}{\|\Delta_{i,\mathbf{y},\hat{\mathbf{y}}}\|^2} \right\} .$$

- Set

$$\boldsymbol{\mu}_{i+1} = \boldsymbol{\mu}_i + \alpha_i \Delta_{i,\mathbf{y},\hat{\mathbf{y}}}$$

Output: Weight vector $\boldsymbol{\mu}_{T+1}$

The update of Eq. (11) can be computed analytically to get a structured version of PA-I :

$$\begin{aligned} \boldsymbol{\mu}_{i+1} &= \boldsymbol{\mu}_i + \alpha_i \Delta_{i,\mathbf{y},\hat{\mathbf{y}}} , \\ \alpha_i &= \min \left\{ C, \frac{\max \{0, \ell(y_i, \hat{y}_i) - \boldsymbol{\mu}_i \cdot \Delta_{i,\mathbf{y},\hat{\mathbf{y}}}\}}{\|\Delta_{i,\mathbf{y},\hat{\mathbf{y}}}\|^2} \right\} . \end{aligned} \quad (12)$$

The algorithm is summarized in Alg. 1. The theoretical properties of this algorithm were analyzed by Crammer et al. (2006), and it was demonstrated on a variety of tasks (e.g. (Chechik et al., 2009)).

Confidence-Weighted Learning Online confidence-weighted (CW) learning (Dredze, Crammer, and Pereira, 2008; Crammer, Dredze, and Pereira, 2008) generalizes the passive-aggressive (PA) update principle to multivariate Gaussian distributions over the weight vectors - $\mathbf{w} \sim \mathcal{N}(\boldsymbol{\mu}, \Sigma)$. Originally, it was designed for binary classification and later was extended to multi-class problems (Crammer, Dredze, and Kulesza, 2009), speech recognition (Crammer, 2010) and sequence prediction (Mejer and Crammer, 2010). We now sketch a generalization for structured problems which contains all previous versions as special cases.

The mean $\boldsymbol{\mu} \in \mathbb{R}^d$ contains the current estimate for the best weight vector, whereas the diagonal Gaussian covariance matrix $\Sigma \in \mathbb{R}^{d \times d}$ captures the confidence in this estimate. More precisely, the diagonal elements $\Sigma_{p,p}$, capture the confidence in the value of the corresponding weight $\boldsymbol{\mu}_p$; the smaller the value of $\Sigma_{p,p}$, is, the more confident is the model in the value of $\boldsymbol{\mu}_p$. Full matrices are

Algorithm 2 Sequence Labeling CW

Input:

- Joint feature mapping $\Phi(\mathbf{x}, \mathbf{y}) \in \mathbb{R}^d$
- Initial variance $a > 0$
- Confidence parameter ϕ

Initialize:

- $\mu_0 = \mathbf{0}$, $\Sigma_0 = aI$

For $i = 1, 2, \dots, T$

- Get input $\mathbf{x}_i \in \mathcal{X}$
- Predict best labeling $\hat{\mathbf{y}}_i = \arg \max_{\mathbf{z}} \mu_{i-1} \cdot \Phi(\mathbf{x}_i, \mathbf{z})$
- Get correct labeling $\mathbf{y}_i \in \mathcal{Y}(\mathbf{x}_i)$
- Define $\Delta_{i,\mathbf{y},\hat{\mathbf{y}}} = \Phi(\mathbf{x}, \mathbf{y}_i) - \Phi(\mathbf{x}, \hat{\mathbf{y}}_i)$
- Compute α_i and β_i using Eq. (15) and Eq. (16)
- Set

$$\begin{aligned} \mu_i &= \mu_{i-1} + \alpha_i \Sigma_{i-1} \Delta_{i,\mathbf{y},\hat{\mathbf{y}}} \\ \Sigma_i^{-1} &= \Sigma_{i-1}^{-1} + \beta_i \text{diag} \left(\Delta_{i,\mathbf{y},\hat{\mathbf{y}}} \Delta_{i,\mathbf{y},\hat{\mathbf{y}}}^\top \right) \end{aligned}$$

Output: Weight vector μ_{T+1} and confidence Σ_{T+1}

not feasible as the dimension is in the order of millions.

CW classifiers are trained according to a PA rule that is modified to track differences in Gaussian distributions. At each round, the new mean and covariance of the weight vector distribution is chosen to be the solution of the following optimization problem,

$$\begin{aligned} (\mu_{i+1}, \Sigma_{i+1}) &= \arg \min_{\mu, \Sigma} D_{\text{KL}}(\mathcal{N}(\mu, \Sigma) \parallel \mathcal{N}(\mu_i, \Sigma_i)) \\ s.t. \quad Pr[\Delta_{i,\mathbf{y},\hat{\mathbf{y}}} \cdot \mathbf{w} \geq 0] &\geq \Psi(\phi \ell(y_i, \hat{y}_i)) \end{aligned} \quad (13)$$

where Ψ is the cumulative function of the normal distribution and $\phi > 0$ controls the tradeoff between adjusting the model according to last example and being close to the old weight vector distribution. The larger the loss is, the larger probability we require for the event $\Delta_{i,\mathbf{y},\hat{\mathbf{y}}} \cdot \mathbf{w} \geq 0$.

The solution for the CW updates is of the form,

$$\begin{aligned} \mu_i &= \mu_{i-1} + \alpha_i \Sigma_{i-1} \Delta_{i,\mathbf{y},\hat{\mathbf{y}}} \\ \Sigma_i^{-1} &= \Sigma_{i-1}^{-1} + \beta_i \text{diag} \left(\Delta_{i,\mathbf{y},\hat{\mathbf{y}}} \Delta_{i,\mathbf{y},\hat{\mathbf{y}}}^\top \right) \end{aligned} \quad (14)$$

where $\text{diag}(A)$ return a diagonal matrix which equals to the diagonal elements of the matrix A . The two scalars α_i and β_i are computed using the mean and variance of the margin,

$$v_i = \Delta_{i,\mathbf{y},\hat{\mathbf{y}}}^\top \Sigma_i \Delta_{i,\mathbf{y},\hat{\mathbf{y}}} , \quad m_i = \mu_i \cdot \Delta_{i,\mathbf{y},\hat{\mathbf{y}}} , \quad (15)$$

Dataset	Sentences	Words	Features
NP chunking	11.0 K	259.0 K	1.35 M
NER English	17.5 K	250.0 K	1.76 M
NER Spanish	10.2 K	317.6 K	1.85 M
NER Dutch	21.0 K	271.5 K	1.76 M

Table 2: Properties of sequences labeling datasets.

and are,

$$\begin{aligned}
\phi_\ell &= \phi_\ell(y_i, \hat{y}_i) , \quad \phi' = 1 + \phi_\ell^2/2 , \quad \phi'' = 1 + \phi_\ell^2 \\
\alpha_i &= \max \left\{ 0, \frac{1}{v_i \phi''} \left(-m_i \phi' + \sqrt{m_i^2 \frac{\phi_\ell^4}{4} + v_i \phi_\ell^2 \phi''} \right) \right\} \\
\beta_i &= \frac{\alpha_i \phi_\ell}{\sqrt{v_i^+}} \quad , \quad v_i^+ = \frac{1}{4} \left(-\alpha_i v_i \phi_\ell + \sqrt{\alpha_i^2 v_i^2 \phi_\ell^2 + 4 v_i} \right)^2 . \quad (16)
\end{aligned}$$

The method presented here is called *1-best* binary reduction since the binary example for the update step at each round was generated as the difference between a single prediction, the model’s best prediction, and the true labeling. There are variants of this method that at each round utilize multiple predictions, usually the *n-best* predictions, to generate multiple binary examples for updating the model. Please see (Crammer, Mcdonald, and Pereira, 2005; McDonald, Crammer, and Pereira, 2005b) for more details.

Finally, we used parameter averaging with both algorithms. That is, during test time we are not using the final parameter vector $\boldsymbol{\mu}_{T+1}$, but instead using its average $(\sum_t \boldsymbol{\mu}_t)/(T+1)$. It was shown to improve performance in other settings, and for us it either improved performance a bit, or did not make it worse.

5 Data

We evaluated our algorithms on two types of structured predictions problems: sequence labeling and dependency parsing. For the sequence labeling experiments we used four large sequential classification datasets taken from the CoNLL-2000, 2002 and 2003 shared tasks: noun-phrase (NP) chunking (Kim, Buchholz, and Sang, 2000), and named-entity recognition (NER) in Spanish, Dutch (Tjong and Sang, 2002) and English (Tjong, Sang, and Meulder, 2003). The properties of the four datasets are summarized in Table 2. For the task of NP chunking we used the BIO system of labeling marking the first word (beginning) of a phrase (B), additional words of a phrase (in a phrase; I) and other words (O). For NER problems we used the same system for the four categories ending up with nine possible labels. Eight labels are the beginning of a name-entity (B)

Dataset	Sentences	Words	Features
Arabic	1.5 K	54.3 K	1.03 M
Bulgarian	12.8 K	190.2 K	2.64 M
Chinese	56.0 K	337.1 K	4.92 M
Czech	72.7 K	1,249.0 K	12.69 M
Danish	5.2 K	94.3 K	1.22 M
Dutch	13.3 K	195.0 K	2.36 M
English	39.8 K	950.0 K	7.00 M
German	39.2 K	699.6 K	6.99 M
Japanese	17.4 K	151.4 K	0.85 M
Portuguese	9.0 K	206.6 K	2.50 M
Slovene	1.5 K	28.7 K	0.55 M
Spanish	3.3 K	89.3 K	1.40 M
Swedish	11.0 K	191.4 K	2.50 M
Turkish	5.0 K	57.5 K	1.10 M

Table 3: Properties of dependency parsing datasets.

or being in it (I) for every the four categories: Location, Organization, Person and Miscellaneous. The ninth label is marking O(ther) words.

We followed previous feature generation process (Sha and Pereira, 2003). For NP chunking we used word and part-of-speech over a window of size (5) centered at the word to be labeled. For NER we used word and standard sub-word features including word, part-of-speech, suffix and prefix identity as well as standard orthographic features (e.g. word is capitalized), with all features over a window of size five (5) centered around the word at investigation.

To evaluate the task of dependency parsing we used 14 datasets: 13 languages used in CoNLL 2006 shared task (Arabic, Bulgarian, Chinese, Czech, Danish, Dutch, German, Japanese, Portuguese, Slovene, Spanish, Swedish and Turkish¹, and the English Penn Treebank. The properties of the datasets are summarized in Table 3 The feature representation of edges between words is generated as a combination of the connected words, the part-of-speech of the words and their local context, that is words before, after and between the connected words, the direction of the dependency (left or right) and the distance between the words (for more details see (McDonald, Crammer, and Pereira, 2005b)). For dependency parsing evaluation we used a single split of training, development and testing sets for each language. The number of sentences in the training datasets is ranging between 1.5 – 72K, with an average of 20K sentences, 30K – 1.2M words and 0.5 – 12.7M features. The test sets contain ~400 sentences and ~6K words for all datasets, except English with 2.3K sentences and 55K words.

¹See <http://nextens.uvt.nl/~conll/> for details

	CW	5-best PA	Perceptron
NP chunking	0.947	0.946	**0.944
NER English	0.877	* 0.870	* 0.862
NER Dutch	0.787	0.784	* 0.761
NER Spanish	0.774	0.773	* 0.756

Table 4: Averaged F-measure of methods. Statistical significance (t-test) are with respect to CW, where * indicates 0.001 and ** indicates 0.01

6 Prediction Performance Evaluation

Our primary goal is developing new methods to estimate confidence in prediction, not prediction perse. Yet prediction itself is the end goal of learning. Furthermore, we could not find published performance evaluation of CW on structured prediction tasks, and the results below are among such first results. We thus briefly report for completeness the performance of CW comparing it with previous state-of-the-art online algorithms. Below we report in details the results of our evaluation of various confidence estimation algorithms. Our goal was to evaluate whether CW improves performance for these structured prediction tasks as it does for binary classification (Dredze, Crammer, and Pereira, 2008; Crammer, Dredze, and Pereira, 2008) and multiclass prediction (Crammer, Dredze, and Kulesza, 2009). As our goal is confidence and not achieving the best accuracy we note that the performance results we report now are not necessarily the best published in the literature as they are obtained by using existing tools, and specifically MSTParser "out of the box" not incorporating recent parsing advancements.

We compared the performance of CW Alg. 2 with the passive-aggressive algorithm, which was shown to be a state-of-the art in both tasks. Specifically, we used 5-best PA (the value of five was shown to be optimal for various tasks (Crammer, McDonald, and Pereira, 2005)) for sequence labeling and 1-best PA which is the training algorithm MSTParser uses for non-projective parsing (McDonald et al., 2005). Additionally, we include the performance of the Averaged-Perceptron algorithm on the sequence prediction tasks to show various properties of all algorithms. It is omitted for parsing as it was shown to be inferior to PA (McDonald et al., 2005). We ran CW with a diagonal covariance matrix, as full matrix is not feasible. Specifically, we used the update rule for full matrices and then removed the off-diagonal elements². We used parameter averaging with all methods, including CW, as it improved performance for all algorithms, especially on parsing.

We used 10-fold cross validation for sequence labeling and existing split of data into training, development and test set for parsing. Hyper-parameters (ϕ

²This was shown to perform the best compared with two other alternatives: update a full *inverse* Σ and remove its off-diagonal elements, and compute an exact update for a diagonal covariance matrix.

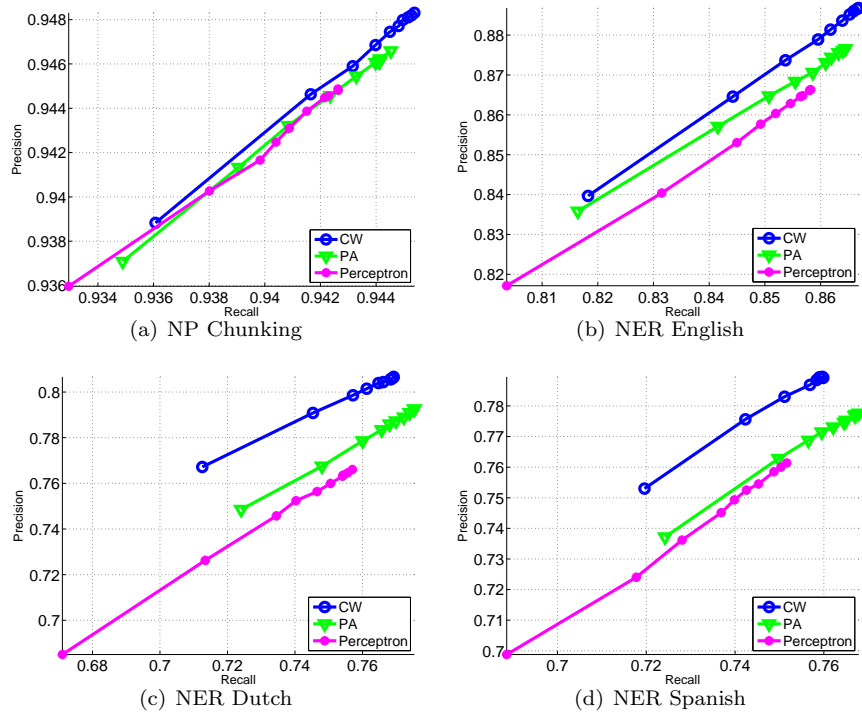


Figure 5: Precision and Recall on four datasets (four panels). Each connected set of ten points corresponds to the performance of a specific algorithm after each of the 10 iterations, increasing from bottom-left to top-right.

for CW, C for PA) were tuned for each sequence prediction task using a single run over a random split of the data into a three-fourths training set and a one-fourth test set and using a development set with 200 sentences per language for parsing. All algorithms were executed for ten (10) iterations over the training set.

6.1 Sequence Labeling Performance Evaluation

The F-measure of all algorithms after 10 iterations is summarized in Table 4. In all four datasets CW algorithm outperforms PA that outperforms the Perceptron algorithm. The difference between CW and the Perceptron is statistically significant using paired t-test over the 10 folds, and between CW and PA it is significant in one dataset.

We further investigate the convergence properties of the algorithms in Fig. 5 in which we plot the recall and precision evaluated after each training round averaged across the 10 folds. Each panel summarizes the results for a single dataset, and in each panel a single set of connected points corresponds to one

Dataset	Edge Accuracy		Complete Trees	
	CW	1-best PA	CW	1-best PA
Arabic	0.777	0.772	0.110	0.123
Bulgarian	0.899	0.898	0.410	0.397
Chinese	0.901	0.900	0.739	0.737
Czech	0.845	0.844	0.340	0.323
Danish	0.878	0.871	0.326	0.304
Dutch	0.830	0.831	0.282	0.282
English	0.888	0.889	0.292	0.287
German	0.886	0.888	0.412	0.409
Japanese	0.936	0.940	0.769	0.779
Portuguese	0.863	0.863	0.302	0.302
Slovene	0.782	0.777	0.266	0.256
Spanish	0.820	0.813	0.189	0.180
Swedish	0.865	0.866	0.404	0.391
Turkish	0.781	0.776	0.281	0.276
Average	0.854	0.852	0.366	0.360

Table 5: Accuracy of predicted edges (two left columns) and percentage of complete trees (two right columns) of parser trained with CW and PA.

algorithm. Points in the left-bottom of the plot correspond to early iterations and points in the right-top correspond to later iterations. Long segments indicate a big improvement in performance between two consecutive iterations.

High (in the y-axis) values indicate better precision and right (in the x-axis) values indicate better recall. The performance of all algorithms is converging in about 10 iterations as indicated by the fact the points in the top-right of the plot are close to each other. The long segments in the bottom-left for the Perceptron algorithm indicate that this algorithm benefits more from more than one pass compared with the other algorithms. Interestingly, in NER Dutch and NER Spanish (two bottom panels), PA achieves slightly better recall than CW but is paying in terms of precision and overall F-measure performance.

6.2 Dependency Parsing Performance Evaluation

Predicted edges accuracy of PA and CW are summarized in Table 5. The accuracy ranges from 77% on Arabic to 94% on Japanese, with an average of 85%. Training the parser with CW algorithm compared to PA yield a small accuracy improvement in 8 of 14 languages, with maximal improvement of 0.7% for Danish and Spanish and maximal degradation of 0.4% for Japanese. The accuracy averaged over all the languages using CW is 85.4% compared to 85.2% achieved by PA. The percentage of *complete – trees*, that is sentences where the parse tree was completely correct, was also improved by CW compared to PA in 10 of 14 languages, and averaged over all the languages the parser trained

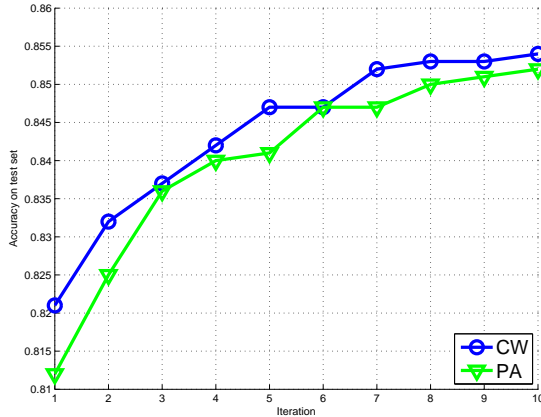


Figure 6: Parsing accuracy of PA and CW vs. iteration averaged over all 14 languages.

with CW got 36.6% complete trees compared to 36.0%.

We investigate the convergence results of the two algorithm in Fig. 6 where we plot the accuracy results (averaged over all the language) evaluated using the test set after each training iteration. After a single pass over the training data CW algorithm performs better than PA, achieving higher accuracy on 11 of 14 datasets and average accuracy of 82.1% compared to 81.2%. With additional passes over training data the performance gap is reduced, until finally after ten iteration PA closes most of the gap and achieves average accuracy lower than CW by only 0.2%.

To conclude, in all tasks of sequence labeling and most tasks of dependency parsing, CW slightly improves over PA; which is also reflected in its averaged performance which is slightly better than the averaged performance of PA. Additionally, CW obtain high-performance after a single round, and benefit less from multiple iterations over data, as opposed to both PA and the Perceptron algorithm. This relation are consistent with previous evaluation of CW on both binary classification (Dredze, Crammer, and Pereira, 2008; Crammer, Dredze, and Pereira, 2008), multi-class prediction (Crammer, Dredze, and Kulesza, 2009) and phoneme-recognition (Crammer, 2010). Yet, in all these previous work the improvement of CW over both PA and Perceptron was higher than the improvement we found here for sequence labeling and parsing. Currently, it is not clear why CW improves more over PA in the context of multi-class and binary prediction, and less in the context of structured prediction. One possible explanation is that implicitly CW exploits feature statistics. In the former simple problems the features are orthogonal per class, while in structured prediction, the features are sum over parts (as in Eq. (4)) and thus may have different statistical properties, such as dependencies.

7 Confidence Estimation Methods Evaluation

We now report an evaluation of the confidence estimation methods mentioned above. We trained a classifier using the CW algorithm running for ten (10) iterations on the training set and applied it to the testing set to obtain an initial labeling, the hyper-parameter ϕ was set to its optimal value obtained in the experiments reported in Sec. 6. We then applied each of the confidence estimation methods on all the testing set labels. For sequences, a single split of four-fifths of the data was used as training set and the remaining one-fifth as testing set. For parsing we used the given split of the data into a training set and a test set as described above. For sequences, the fraction of words for which the trained model made a mistake ranges between 2% (for NER Dutch) to 4.1% (for NER Spanish). While for parsing the fraction of incorrect edges is between 23% (for Arabic) to 6% (for Japanese), with an average of 15%.

Six algorithms and one baseline were evaluated. The baseline is random confidence scores for all the labels. The margin based method called **Delta** described in Sec. 3.1. The marginal based method called **Gamma** described in Sec. 3.2, and four methods based on alternatives described in Sec. 3.3. Two of these methods are based on top-K best prediction defined in Sec. 3.3.1, one using the output of the prediction algorithm as is called KB (*K*-best) defined in Eq. (8), and the other is based on weighting its output called WKB (weighted *K*-best) defined in Eq. (9). The other two alternatives-based methods are using stochastic models both described in Sec. 3.3.2. The first by inducing a Gaussian distribution over weights with covariance sI called KD-Fix for K draws with fixed covariance, and the second by using the scaled covariance matrix learned by CW called KD-PC for K -draws by parameter confidence.

For the KD-PC algorithm we note that the predictions of the CW algorithm are based solely on the mean weight vector $\hat{\mathbf{y}} = \arg \max_{\mathbf{z}} \boldsymbol{\mu} \cdot \boldsymbol{\Phi}(\mathbf{x}, \mathbf{z})$ and are invariant to initial scale a of the covariance aI (as was noted elsewhere (Crammer, Dredze, and Pereira, 2008)). Nevertheless, for the purpose of confidence estimation the scale of the covariance Σ has a huge impact. Small eigenvalue of Σ yield that all the samples of Z in Eq. (10) will be the same, while large values yield almost complete random vectors, ignoring the mean.

One possible simple option is to run CW few times with few possible initializations of the covariance Σ and choose one copy based on the confidence evaluated on the training set. However, since the actual predictions of all these versions is the same and all the resulting covariance matrices will be proportional to each other (Crammer, Dredze, and Pereira, 2008, Lemma 3) in practice we run the algorithm only once initializing the covariance with I . Then, after training is completed, we pick the best covariance matrix of the form $s\Sigma$ for a positive scalar s where Σ is the covariance output with initialization I , and choose the best value s using the training set.

The parameters of the confidence estimation methods: size of K of the number of labelings used in the four first methods (KD-PC, KD-Fix, KB, WKB), the weighting scalar s used in KD-PC and KD-Fix, and the coefficient c of the **Gamma** method were tuned for each dataset on a development set according to

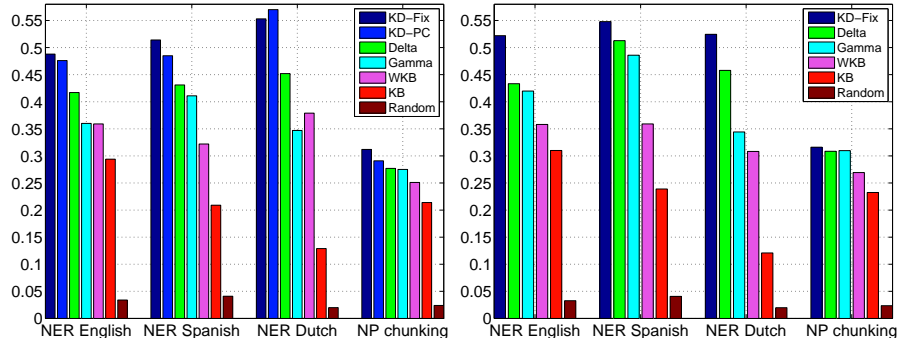


Figure 7: Average precision of rankings of the words of the test-set according to confidence in the prediction of all methods (left to right bars in each group): KD-Fix, KD-PC, Delta, Gamma, WKB, KB and random ordering, when training with the CW algorithm (left) and the PA algorithm (right).

the best measured *average precision* achieved in the task of incorrect prediction detection, described in Sec. 7.1.

We tried 20 values in the range 0.01 to 1.0 for the parameter s . For the number of labeling K the values in 10, 20...80 were used. For the K-Draws methods, larger K generally improved performance up to about $K = 50$ with flat performance beyond that, so $K = 50$ was set for all datasets (see also Sec. 7.3). The **K-Best** and **WK-Best** methods are more sensitive to value of K and values between 10 to 30 were used across the different datasets. Performance degraded significantly for larger values of K . For the c parameter of **Gamma** method 30 values between 0.01 to 3.0 were tried.

We evaluate the algorithms in two aspects of confidence: relative confidence (Sec. 7.1) and absolute confidence (Sec. 7.2) and two application: precision-recall tradeoff (Sec. 8.1) and active learning (Sec. 8.2).

7.1 Relative Confidence

In this experiment confidence estimation methods are evaluated in accordance to their ability to rank all the words in the test set (per dataset) having words for which there is a prediction mistake in the top and the correct predictions in the bottom. Conceptually, this task can be thought of as a retrieval task of the erroneous words. All words were ranked from low to high according to the confidence score in the prediction associated with each word by the various confidence methods. Then their performance in the task was evaluated in a few ways. We split the results according to the task type.

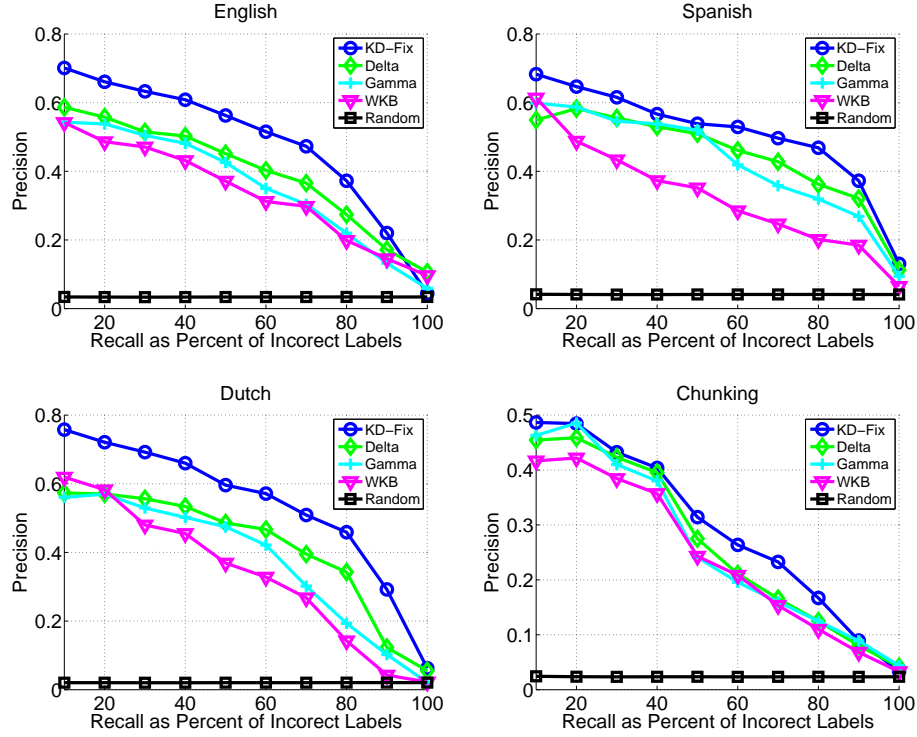


Figure 8: Precision in detection of incorrect labels as recall increases on three NER tasks and NP chunking in English.

7.1.1 Sequence Labeling

The average precision for ranking the words of the test-set according the confidence in the prediction for the seven methods in sequence labeling is summarized in the left panel of Fig. 7 when training with CW. The algorithms are ordered from left-to-right: KD-Fix, KD-PC, Delta, Gamma, WKB, KB and random ordering. The average precision is computed by averaging the individual precision values computed at all ranks of erroneous words.

From the plot we observe that when having a random ordering the average precision is about the frequency of erroneous word, and clearly random ordering achieves the lowest (worst) average precision. The next two best methods are these based on K-Best predictions, where the weighted approach WKB outperforms the non-weighted version KB. Thus, using the actual score value into consideration improves the ability to detect erroneous words. Next in performance are Gamma and Delta, the margin-based and marginal-probabilities methods that outperform the K-best methods in all four datasets. Delta is better than Gamma in two of the dataset and equal in the other two. The two best performing methods are KD-Fix and KD-PC, where the former is better in

three out of four datasets. The relative success of **KD-Fix** compared to **KD-PC** is surprising, as **KD-Fix** does not take into consideration the actual uncertainty in the parameters learned by **CW**, and in fact replaces it with a *fixed* value across all features.

Except for **KD-PC** that takes the parameter confidence information into consideration, all the other confidence estimation methods do not assume a confidence-based learning approach. We thus repeated the experiment using the passive-aggressive algorithm (**PA**) rather than **CW** for training the model. The results appear in the right panel of Fig. 7 and basically tell the same story: **KD-Fix** outperforms the margin-based and marginal-probabilities methods **Delta** and **Gamma**, and the K-Best Viterbi based methods, **KB** and **WKB** achieve lowest performance with the weighted version better than the non-weighted. Note that in general **CW** is slightly better than **PA** in the prediction task (Sec. 6) and thus retrieval of erroneous words on the set labeled by the **PA** model is slightly an easier task, this may explain some of the bars in the right panel are higher than their corresponding bars in the left panel.

Average precision does not tell the whole story - it encapsulates the detection of all the incorrect edges into a single number. More refined analysis is described via precision-recall (**PR**) plots showing the precision as more incorrect labels are detected. **PR** plots for model trained with **CW** algorithm are shown in Fig. 8. The plots for **KD-PC** and **KB** are omitted for clarity, **KD-PC** curve is very similar to **KD-Fix** and **KB** is worse than all the rest. The plots present the incorrect-labels detection precision in different recall values from 10% to 100%. We observe that the advantage of the K-Draws methods over other methods is consistent throughout the entire retrieval process. Interestingly, for low recall values of around 10%, in **NER** in Dutch and Spanish, **WKB** performed better than **Delta** and **Gamma**, yet its performance quickly degraded for higher recall values.

To illustrate the effectiveness of the incorrect labels detection process Table 6 presents the number of incorrect labels detected vs. number of labels inspected for English **NER** dataset. The test set for this task includes 50K words and the classifier made mistake on only 1,650 words, that is, accuracy of 96.7%. We show the number of incorrect labels detected after inspecting 500, 2,500 and 5,000 labels which are 1,5 and 10% of all labels. When using random inspection, the number of incorrect labels detected is, as expected, 1%, 5% and 10% of all mislabeled words. Yet when inspecting the labels according to the ranking induced by **KD-Fix** method, 20%, 70% and 86% of all mislabeled words were detected for the same effort.

7.1.2 Dependency Parsing

We applied the same methodology for evaluating the confidence estimation methods in the task of dependency parsing. Here, all predicted edges were ranked according to their confidence score ordered from low to high, and ideally, erroneous edges by the parser are ranked at the top. A summary of the average precision, computed at all ranks of erroneous edges, evaluated for all confidence estimation methods and all the 14 datasets is summarized in Table 7.

Words inspected (% of total)	KD-Fix	Delta	Random
500 (1%)	336 (20%)	278 (17%)	15 (0.9%)
2,500 (5%)	1,148 (70%)	1,003 (61%)	83 (5%)
5,000 (10%)	1,415 (86%)	1,310 (79%)	164 (9.9%)

Table 6: Number of incorrect labels detected, and the corresponding percentage of *all mistakes*, after inspecting 500–5,000 labels which are 1–10% of all labels, using random ranking and ranking induced by KD-Fix and Delta methods.

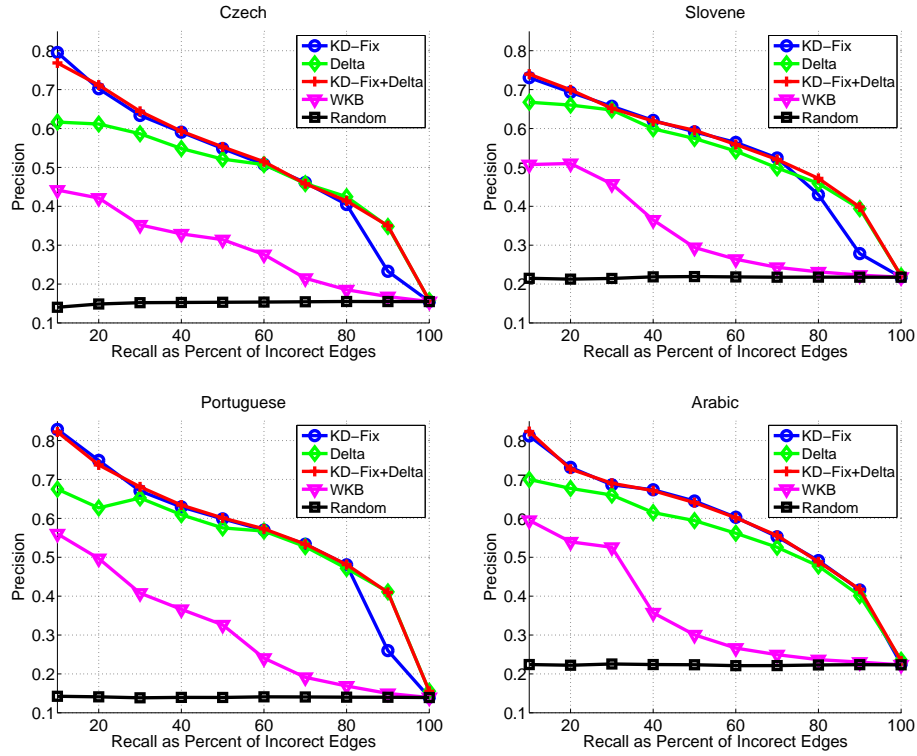


Figure 9: Precision in detection of incorrect edges as recall increases on four dependency parsing datasets. KD-PC curves are very similar to KD-Fix and omitted for clarity.

The average precision achieved by random ordering is lower than all the methods and is about equal to the error rate for each dataset. Next are the K-Best methods, where the weighted version performs better than the non-weighted version. The margin-based Delta method improves significantly over the the K-Best methods. Finally, KD-fix and KD-PC methods achieve the best

performance with **KD-Fix** a little better than **KD-PC**, and both **K-Draws** methods outperform **Delta** method on average and in 12 of 14 datasets. These results are consistent with the results observed for sequence labeling.

The Precision-Recall (PR) plots for several datasets are shown in Fig. 9 and provide deeper insight of the mistakes detection precision as more incorrect-edges are detected. (**KD-PC** plots are very similar to **KD-Fix** and omitted for clarity.) We observe that in most datasets **KD-Fix** performs significantly better than **Delta** in the early detection stage (first 10 – 20% of the incorrect edges), while **Delta** performs better in late detection stages - the last 10 – 20% of the incorrect edges. The second and third rows of Table 8 summarizes the precision obtained by all methods after detecting only 10% incorrect edges and after detecting 90% of the incorrect edges, averaged over all the datasets. (The first row of Table 8 summarized the average-precision averaged over all 14 languages, and is copied from the last row of Table 7 for easier reference.) For example, in three datasets (Czech, Slovene and Portuguese) of Fig. 9, we observe an advantage of **KD-Fix** for low recall and an advantage of **Delta** in high recall. This observation is consistent with most other dataset not shown in these plots. Yet, in few languages, Arabic for example, **KD-Fix** outperforms or equal to **Delta** along the entire range of recall values. This phenomena was not observed for sequence labeling tasks where we found the **K-Draws** method to outperform the other methods throughout the entire retrieval process.

This phenomena emerges from the different properties of the two algorithms. **KD-Fix** assigns at most K distinct confidence values to each edge - the number of models that agreed on that particular edge. As is, there is no mechanism to break ties (in each of the $K + 1$ levels) and thus edges that are assigned with the same confidence level are ordered *randomly* relative to each other. Furthermore, in most datasets large fraction of the edges, $\sim 70 - 80\%$, are assigned to one of the top-three possible confidence scores (i.e. $(K - 2)/K, (K - 1)/K, 1$). As a results, the precision performance of **KD-Fix** drops sharply for recall values of 80% and above. This can be seen by the fast decrease of the line with circle markers in three of plots in Fig. 9, except Arabic. On the other hand, we hypothesize that the low precision values obtained by **Delta** at low recall values (diamond in Fig. 9) is because **Delta** takes into account only two parses, the margin between the highest scoring edge (the predicted edge) and the second best edge, ignoring information about additional edges with score close to the highest score. In contrast, **KD-Fix** integrates scores of K parse tress. In other words, **Delta** is more sensitive to small perturbations of score values compared with **KD-Fix**.

Based on this observation we propose combining both **KD-Fix** and **Delta**. The new method sets the confidence score of an edge to be a weighted mean of the score values of **KD-Fix** and **Delta**, with weights a and $1-a$, respectively, for a value of $a \approx 1$. If the confidence value of two edges according to **KD-Fix** is different, the contribution of the score outputted by **Delta** is negligible, and the final score is very close to the score of only **KD-Fix**. On the other hand, if the score of **KD-Fix** is the same, as happen for large recall values, then **Delta** breaks arbitrary ties. In other words, when ordering all edges according to the

	KD-Fix	KD-PC	Delta	WKB	KB	KD-Fix + Delta	Random
Arabic	0.621	0.623	0.565	0.373	0.366	0.622	0.223
Bulgarian	0.491	0.466	0.463	0.257	0.238	0.494	0.102
Chinese	0.465	0.466	0.452	0.190	0.150	0.473	0.102
Czech	0.539	0.548	0.506	0.301	0.290	0.555	0.152
Danish	0.502	0.497	0.460	0.303	0.280	0.499	0.124
Dutch	0.534	0.536	0.527	0.370	0.358	0.544	0.167
English	0.489	0.459	0.477	0.291	0.278	0.496	0.112
German	0.426	0.418	0.469	0.254	0.232	0.472	0.114
Japanese	0.512	0.525	0.535	0.235	0.151	0.541	0.064
Portuguese	0.586	0.570	0.559	0.323	0.311	0.606	0.143
Slovene	0.561	0.573	0.555	0.345	0.332	0.581	0.218
Spanish	0.637	0.634	0.592	0.351	0.342	0.644	0.184
Swedish	0.528	0.533	0.496	0.289	0.273	0.527	0.137
Turkish	0.603	0.590	0.589	0.372	0.342	0.609	0.221
Average	0.535	0.531	0.518	0.304	0.282	0.547	0.147

Table 7: Average precision in ranking all edges according to confidence values.

new method, we first order edges according to confidence score of **KD-Fix**, then a secondary order is employed according to the confidence values of **Delta** among edges assigned same confidence score by **KD-Fix**. Not surprisingly, we name this method **KD-Fix+Delta**.

This new method enjoys the good of the two methods. As the results show in Table 8 it achieves the highest average-precision averaged over the 14 datasets. It improves average-precision over **KD-Fix** in 12 of 14 datasets and over **Delta** in all 14 datasets. From the second and third row of Table 8, we see that it has Precision very close to **KD-Fix** for recall of 10% (0.729 vs. 0.724), and very close to **Delta** for recall of 90% (0.351 vs. 0.348). Moving to Fig. 9, we observe that the curve associated with the new method (red ticks) is in general as high as the curves associated with **KD-Fix** for low values of recall, and as high as the curves associated with **Delta** for large values of recall.

Finally, similar to sequence labeling task, in dependency parsing all confidence estimation methods, except for **KD-PC**, can be used with a model that does not maintain parameters confidence information. We repeated the experiment but now training a model with the passive-aggressive algorithm, rather than CW. The results appear in the fourth row of Table 8. The results based on PA are consistent with the results based on CW, **KD-Fix** outperforms the margin-based and the K-Best trees methods, and combining **KD-Fix** and **Delta** improves the performance.

	KD-Fix	KD-PC	Delta	WKB	KB	KD-Fix + Delta	Random
Avg-Prec	0.535	0.531	0.518	0.304	0.282	0.547	0.147
Prec @10%	0.729	0.723	0.644	0.470	0.441	0.724	0.145
Prec @90%	0.270	0.279	0.351	0.157	0.151	0.348	0.147
Avg-Prec (PA)	0.539	-	0.513	0.305	0.278	0.548	0.149

Table 8: Row 1: Average precision in ranking all edges according to confidence values, average over all 14 languages. Rows 2-3: Precision in detection of incorrect edges when detected 10% and 90% of all the incorrect edges. Row 4: Average precision in ranking all edges according to confidence values, average over all 14 languages, using PA training.

	KD-Fix	KD-PC	Gamma	WKB	Random
NER English	0.036	0.021	0.053	0.108	0.548
NER Dutch	0.049	0.024	0.046	0.104	0.559
NER Spanish	0.034	0.030	0.049	0.046	0.543
NP Chunking	0.022	0.020	0.019	0.056	0.557
Average	0.035	0.024	0.042	0.078	0.552

Table 9: Root mean square error (RMSE) of the absolute confidence value by the confidence estimation methods for model trained with CW for sequence labeling tasks.

7.2 Absolute Confidence

A second aspect of confidence prediction is the individual confidence values outputted by the various methods, rather than only comparing pairs of values. As before, suitable confidence estimation methods were applied on the entire set of predicted labels³. For every dataset and every algorithm we grouped the words according to the value of their confidence. Specifically, we used twenty (20) bins dividing uniformly the confidence range into intervals of size 0.05. For each bin, we computed the fraction of words predicted correctly from the words assigned to that bin. Ultimately, the value of the computed frequency should be about the center value of the interval of the bin. Formally, bin indexed j contains words with confidence value in the range $[(j-1)/20, j/20)$ for $j = 1 \dots 20$. Let b_j be the center value of bin j , that is $b_j = j/20 - 1/40$. The frequency of correct words in bin j , denoted by c_j is the fraction of words with confidence $\nu \in [(j-1)/20, j/20)$ that their assigned label is correct. Ultimately, these two

³The output of the **Delta** method can not be interpreted on their own, only relatively. In the context of binary classification there are few methods to generate absolute confidence from relative one (Platt, 1998) using a sigmoid function. Yet, it could not be tuned properly in our setting since we tuned all methods according to their performance in *relative* confidence scenario (average-precision for ranking), where all parameters of Platt’s method perform equally good.

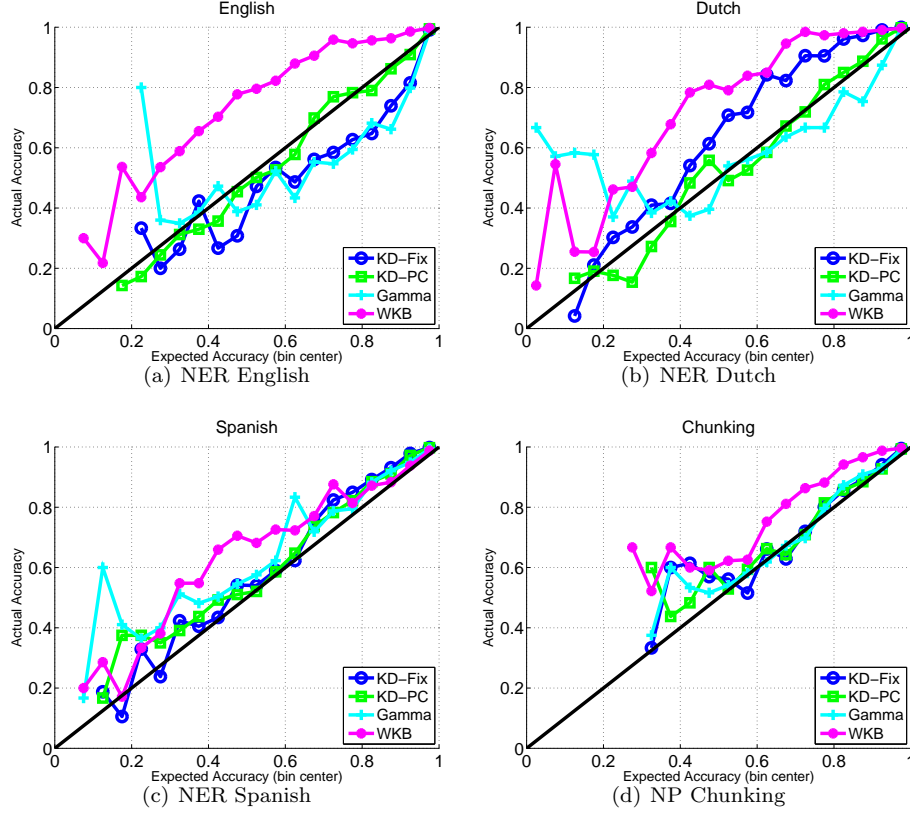


Figure 10: Predicted accuracy vs. actual accuracy in each bin. Best performance is obtained by methods close to the line $y = x$ (black line) for four tasks sequential labeling tasks. Four methods are compared: weighted K -Viterbi (WKB), K -draws PC (KD-PC) and K -draws fixed covariance (KD-Fix) and Γ .

values should be the same, $b_j = c_j$, meaning that the confidence information is a good estimator of the frequency of correct predictions. Methods for which $c_j > b_j$ are too pessimistic, predicting too high frequency of erroneous predictions, while methods for which $c_j < b_j$ are too optimistic, predicting too low frequency of erroneous words.

The results for sequence labeling are summarized in Fig. 10 and for dependency parsing in Fig. 12. Each panel in each figure summarizes the results for a single task (or language in parsing), where the value of the center-of-bin b_j is plotted vs. the frequency of correct prediction c_j , connecting the points associated with a single algorithm. Best performance is obtained when the resulting line is close to the line $y = x$. Four algorithms are shown: KD-Fix, KD-PC, Γ and WK-Best. The results of the K-Best method were inferior to all other methods and omitted for clarity.

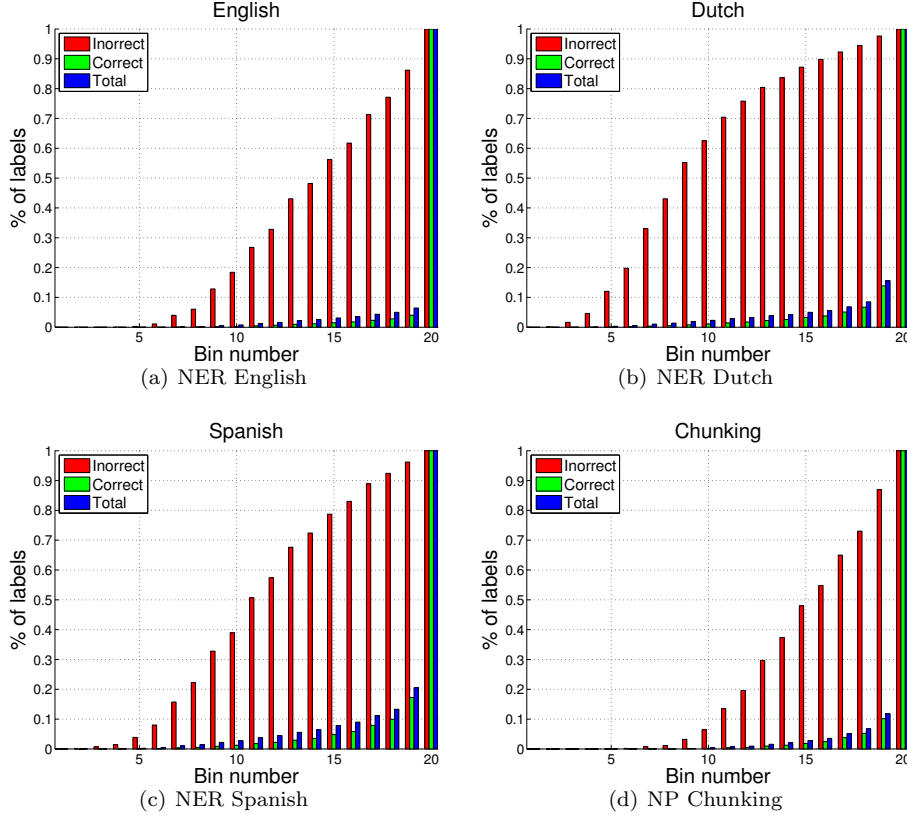


Figure 11: The cumulative distribution of the labels in the bins according to confidence scores assigned by KD-Fix method on the four sequence labeling datasets. Blue bars represent the distribution of all the label in the bins as percentage of total number of labels, green and red bars represent the distribution of correct/incorrect labels as percentage of the *correct/incorrect* labels.

For sequence labeling we observe from the plots that WKB is too pessimistic as its corresponding line is above the line $y = x$. **Gamma** method tracks the line $x = y$ pretty closely in NP-Chunking and NER-Spanish datasets but it is too optimistic in the other two with its corresponding line is below the line $y = x$. The KD-Fix method is too pessimistic on NER-Dutch and too optimistic on NER-English. The best method is KD-PC which tracks the line $x = y$ pretty closely in all four datasets.

For dependency parsing, in most languages KD-Fix and KD-PC methods perform very similarly. The distribution of this qualitative behavior of the KD methods among the 14 datasets is: too optimistic in 2 datasets, too pessimistic in 7 and close to the line $y = x$ in 5 datasets. The confidence scores produced by the WKB method are in general worse than KD-Fix and are too pessimistic

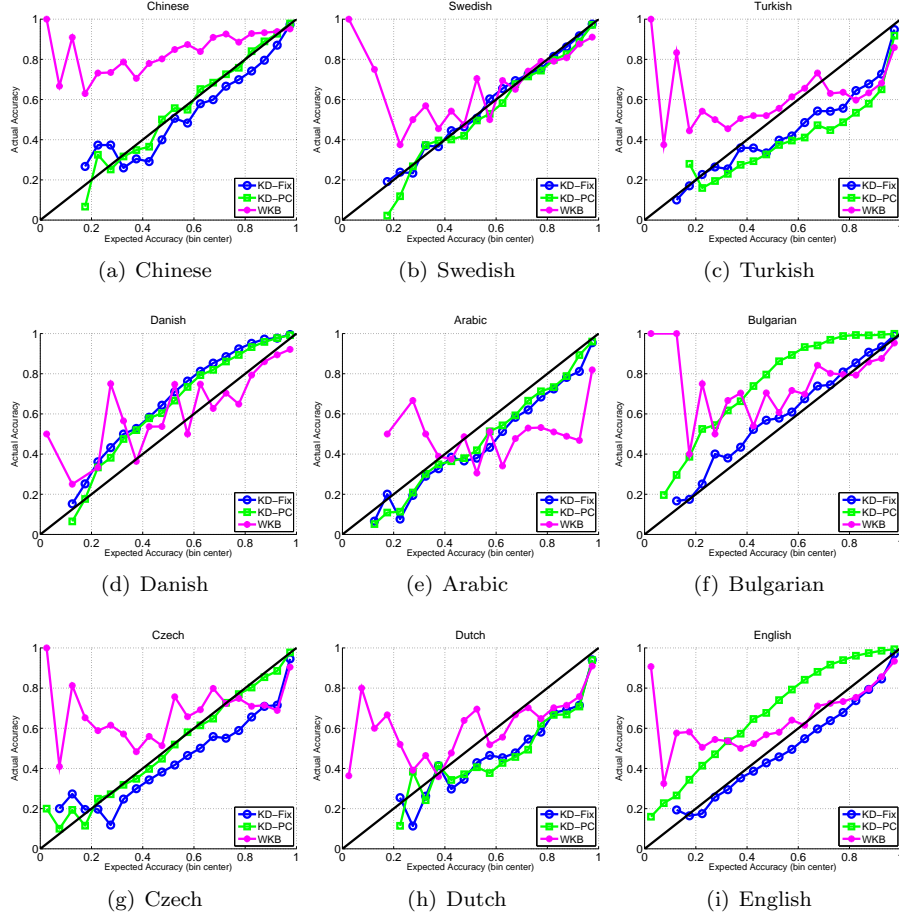


Figure 12: Evaluation of KD-Fix, KD-PC and WK-Best by comparing predicted accuracy vs. actual accuracy in each bin on several of the dependency parsing datasets. Best performance is obtained for curves close to the line $y=x$ (black line).

with the line above $y = x$. In quite a few datasets we observe that WKB is too optimistic in some confidence range and too pessimistic in another range. In most plots both in Fig. 10 and in Fig. 12 the curves on the left (low bin-values) are far from the line $y = x$ and with more fluctuation compared with the right area curves. This is because the left (low confidence) bins are less populated and thus the estimates are noisier.

Fig. 11 shows the distribution of the words in the bins according to confidence scores assigned by KD-Fix method on the four sequence labeling datasets. Blue bars represent the distribution of all the labels in the bins as percentage of total number of labels, green and red bars represent the distribution of cor-

	KD-Fix	KD-PC	WKB	Random
Arabic	0.076	0.057	0.175	0.402
Bulgarian	0.037	0.223	0.093	0.492
Chinese	0.044	0.024	0.223	0.497
Czech	0.087	0.024	0.109	0.451
Danish	0.119	0.095	0.068	0.476
Dutch	0.098	0.105	0.094	0.441
English	0.041	0.144	0.059	0.483
German	0.090	0.094	0.102	0.481
Japanese	0.064	0.039	0.122	0.524
Portuguese	0.099	0.107	0.085	0.465
Slovene	0.156	0.137	0.151	0.404
Spanish	0.083	0.028	0.123	0.429
Swedish	0.023	0.031	0.114	0.465
Turkish	0.105	0.142	0.127	0.404
Average	0.080	0.089	0.117	0.458

Table 10: Root mean square error (RMSE) of the absolute confidence value by the confidence estimation methods for model trained with CW for dependency parsing.

	KD-Fix	KD-PC	Gamma	WKB	Random
Sequences CW	0.035	0.024	0.042	0.078	0.552
Sequences PA	0.031	-	0.039	0.080	0.543
Parsing CW	0.080	0.089	-	0.117	0.458
Parsing PA	0.068	-	-	0.122	0.456

Table 11: Average root mean square error (RMSE) of the absolute confidence value by the confidence estimation methods for models trained with CW and with PA. For sequences the results are averaged over all four datasets and for parsing over all 14 languages.

rect/incorrect labels as percentage of the *correct/incorrect* labels. We see that $\sim 80 - 90\%$ of the labels populate the highest confidence bin, another $\sim 5\%$ populate the second highest bin and the rest of the bins are lightly populated. Among the correct labels even higher percentage is concentrated at the highest confidence bin, while the incorrect labels are distributed more evenly over many of the lower confidence bins.

The predicted vs. actual accuracy plots do not reflect the fact that different bins are not populated uniformly. We thus compute for each method the root

mean-square error (RMSE) in predicting the bin center value given by

$$RMSE = \sqrt{\frac{\sum_j n_j (b_j - c_j)^2}{\sum_j n_j}} ,$$

where n_j is the number of words in the j th bin. The computed RMSE values are presented in Table 11 both sequence labeling and parsing averaged over datasets. We observed a similar trend to the one appeared in the bins plots. For sequences, when using CW for training (top row in Table 11), **WKB** is the least-performing method (after Random), then **Gamma** and **KD-Fix**, where each was better than the other in two datasets, and on average **KD-Fix** achieved lower RMSE. **KD-PC** performed best where it achieved lowest RMSE in three of four datasets and on average. Similar results, obtained when training with PA, appear in the second row of the table. **KD-Fix** achieved lowest RMSE in three of four datasets and on average, and **WKB** performs worst.

For parsing Table 11 presents the RMSE results averaged over all 14 languages, for parser trained with CW (third row) and with PA (fourth row). For CW, both K-Draws methods perform better than **WK-Best**. **KD-Fix** yield lower RMSE than **KD-PC** in seven of the languages and higher in the other seven, and on average **KD-Fix** performed better than **KD-PC** (Table 10 presents results for all languages). This is in oppose to the results observed for sequences where **KD-PC** performed better than **KD-Fix** in all four datasets. When using PA for training, we also see that **KD-Fix** performed better than **WK-Best** method.

To conclude, both **KD-Fix** and **KD-PC** outperform all other methods in both settings and most datasets. The former is slightly better than the later, except in absolute evaluation for sequence labeling.

7.3 Effect of K value on K-Draws methods performance

One of the two parameters that need to be tuned for the K-Draws methods is K , the number of alternative labeling. As discussed above, for each word in each sentence these methods eventually output a single value between zero and one, interpreted as the probability of the prediction being correct. Conceptually, for every word p we associate a coin with probability γ_p . Our goal is to estimate these probabilities up to a satisfying level, denoted by ϵ . These methods are used to estimate the coin's bias by sampling from it, as defined in Eq. (8), $\nu_p = \left| \left\{ i : \hat{y}_p = z_p^{(i)} \right\} \right| / K$. Applying the inequality of Chernoff (1952) and of Hoeffding (1963) we have,

$$\Pr [|\gamma_p - \nu_p| \geq \epsilon] \leq 2 \exp(-2K\epsilon^2) . \quad (17)$$

Denote by N the total number of words in the test set, using the union bound we have,

$$\Pr [\exists \text{ a word } p \text{ s.t. } |\gamma_p - \nu_p| \geq \epsilon] \leq \sum_p \Pr [|\gamma_p - \nu_p| \geq \epsilon] \leq 2N \exp(-2K\epsilon^2) .$$

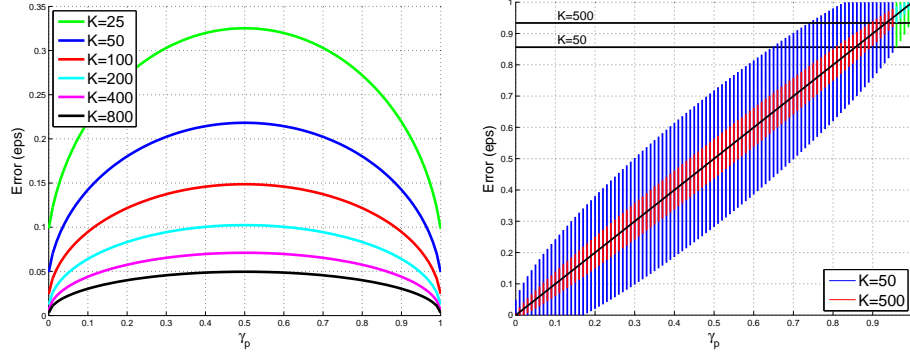


Figure 13: Left: The absolute error bounds for γ_p estimation using KD-Draws method with different number of samples K for $\gamma_p \in [0, 1]$ at confidence level 95%. Right: The interval of possible values for ν_p using $K = 50$ and $K = 500$ at confidence level 95%.

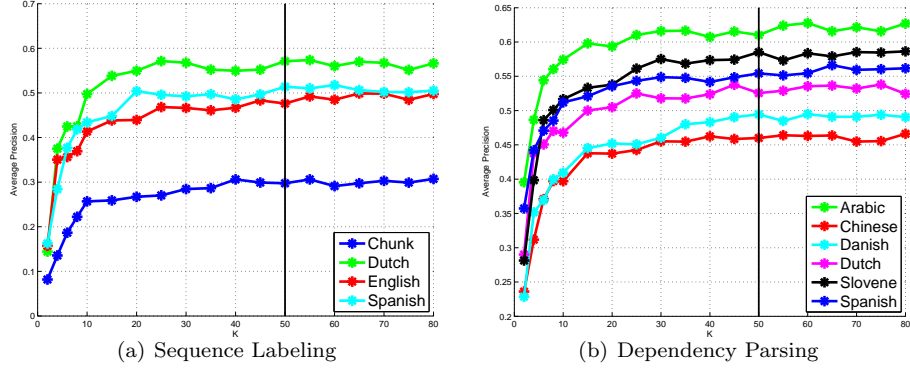


Figure 14: Average precision in ranking all predictions according to confidence scores assigned by KD-Fix method with K value in the range of 2 to 80 for sequence labeling (left) and dependency parsing (right). The black vertical line indicates the value of $K = 50$ used in our experiments.

Let $0 < \delta < 1$ be some confidence level. Then upper bounding the right-hand-side of the last inequality with δ and solving for K we get,

$$K \geq \frac{\log(2N/\delta)}{2\epsilon^2}.$$

Note that if we set ϵ to be the length of a confidence bin, then by setting the value of K to be above the lower bound, we bound the probability that a word will not fall in the correct bin, or one of its two closet neighbors.

Concretely, we used 20 bins, thus we set $\epsilon = 1/20 = 0.05$. Additionally, we set $\delta = 0.05$, and $N = 500,000$ (see Table 2 and Table 3) we get, $K \approx 3,363$.

This estimate is pessimistic in many aspects. First, it is based on the assumption that the estimates ν_p of γ_p are independent, yet this is clearly not the case since features that tie the prediction for few words are used. In the extreme case, where the prediction of all words in a sentence are completely tied (that is, knowing the labeling of one word, induces a deterministic labeling of all other words), then the number of all words N should be replaced with the number of all sentences a typical value of about 25,000, which yields a value of $K \approx 2,764$.

The discussion above is pessimistic in another sense. It assumes we need that all estimates ν_p will be close to their correct values γ_p . However, we are often not interested in estimating the bias values γ_p per-se, but estimating confidence for a practical purpose. For example, in the task of incorrect prediction detection, a good separation between the labels with high and low γ_p values is sufficient and error on the absolute value is acceptable. Therefore we can take the actual value of γ_p into consideration. Using the inequality of Bernshtein (1946) (see also (J.V.Uspensky, 1937)) we have,

$$\Pr[|\gamma_p - \nu_p| \geq \epsilon] \leq 2 \exp \left(-\frac{K\epsilon^2}{2(\gamma_p(1 - \gamma_p) + \epsilon/3)} \right). \quad (18)$$

For γ_p values close to 1 the error is small which allows effective detection of high confidence labels. Comparing the right-hand-side of the last equation to δ/N we solve for the error interval and get a γ -dependent error interval

$$\epsilon(\gamma_p) = \frac{\frac{2}{3}L + \sqrt{(\frac{2}{3}L)^2 + 8KL\gamma_p(1 - \gamma_p)}}{2K}.$$

where $L = \log \frac{2N}{\delta}$. In other words, for each value γ_p we get a different error interval $\epsilon = \epsilon(\gamma_p)$ such that with probability greater than $1 - \delta$ all estimates ν_p falls within the interval $[\gamma_p - \epsilon(\gamma_p), \gamma_p + \epsilon(\gamma_p)]$.

The left plot of Fig. 13 presents error intervals for all γ_p estimated using **KD-Draws** method with different number of samples K with probability greater than 95%. For values of γ_p far from 0.5 the intervals $\epsilon(\gamma_p)$ are low, compared with values of γ_p close to 0.5. The right plot presents for each value of γ_p the interval where its estimate ν_p may fall with high-probability using $K = 50$ (Blue) and $K = 500$ (Red) for confidence level 95%. The two horizontal lines mark (with high-probability) the lowest possible estimate ν_p for $\gamma_p = 0.95$, the lower and upper lines for $K = 50$ and 500 respectively. We see that for $K = 50$ words with $\gamma_p > 0.65$ may have their corresponding estimate ν_p greater than words with $\gamma_p = 0.95$, while when using $K = 500$ only words with $\gamma_p > 0.9$ may have the corresponding estimate ν_p greater than labels with $\gamma_p = 0.95$. This means, for example, that if we are interested in words that their prediction is with high-confident, then when using $K = 500$ and picking all words with $\nu_p > 0.95$ with high probability we will pick only words with $\gamma_p > 0.9$. As expected, greater values of K yield better error estimates so the choice of K should be guided by the application of the confidence scores and the sensitivity

to the estimate accuracy. Additionally, we observed in Fig. 11 that most (more than %90) words have estimates $\nu_p > 0.95$. So for most words the estimates is pretty close to the correct values, which will not affect much the average precision or f-measure.


Although theoretically about $K = 500$ is expected to yield good results, still this value is large for reasonable purposes. We evaluated the affect of K for various values of K and empirically found that for our practical purposes relatively small values of K are sufficient and increasing K beyond these values does not improve performance. Indeed, as mentioned above, for the **K-Draws** methods we set the value of K by picking a best value of K on a *development set* evaluating average precision in the task of incorrect prediction detection. Eventually we set a single value of $K = 50$ for all datasets. Indeed, this value is one order of magnitude smaller than the most optimistic estimate above. One explanation is that the bounds are worst-case in the sense that we assumed that the estimate ν_p will be smaller than γ_p for all words with high-confidence and larger than γ_p for all words with low-confidence. Yet, there is no reason that this will happen in practice for all such words, only for a small fraction of them, and thus smaller values of K yield in practice accurate estimates.

Fig. 14 presents average precision results achieved on the test sets using the **KD-Fix** method with different values of K from 2 to 80 for all sequence labeling tasks and several dependency parsing tasks (the rest of the languages follow the same trend and omitted from the plot for clarity). We observe that even with $K = 2$, only two samples per sentence, the average precision results are better than random ranking in all tasks. As K is increased to 10 the performance is greatly improved. For $K = 10$, despite the very large theoretical estimation error, the results are better than the **K-best** methods for all tasks and for the NER tasks even better than **Gamma** and **Delta**. As K is further increased the results continue to improve, yet at a more moderate rate, until reaching maximal results at $K \approx 30$ for most tasks and results remain steady for larger values of K up to 80. These curves can be used to tradeoff performance (average precision) with time, as the time complexity of this method is linear in K .

8 Applications

Additionally of confidence estimation being useful by itself in some contexts, it is also useful for solving other problems. The next two sections present two example applications built on top of the algorithms presented so far. The first application is using the confidence information to trade-off precision and recall. In Sec. 8.1 we describe a modification of an NER system, allowing it to label less words as named-entities, but ask that the labeling will be with high precision. The second application, presented in Sec. 8.2, is performing active leaning in the context of sequence labeling, using the confidence information as a tool to choose which sentences should be labeled by the annotator.

Input	Morgan	Stanley	uses	Google	services
Output	<i>Per</i>	<i>Per</i>	<i>N</i>	<i>Org</i>	<i>N</i>
Confidence	0.7	0.7	1.0	0.98	1.0


 Confidence threshold = 0.75

Input	Morgan	Stanley	uses	Google	services
Output	<i>N</i>	<i>N</i>	<i>N</i>	<i>Org</i>	<i>N</i>

Figure 15: Example of NER system that discards tags with low confidence scores in order to improve precision possibly by sacrificing recall.

8.1 Precision-Recall Tradeoff

Labeling all words with a specific tag yields maximal recall for that tag, as *all* words occurrence of that tag are labeled correctly, yet with the price of low precision, as many words are tagged wrongly. On the other hand, not labeling even one word (or labeling all word with the special tag of *no tag*) yields maximal precision for all tags, as there is not even a single word that is labeled mistakenly by some tag, yet the precision is zero as none of the words that should be tagged are indeed tagged. Clearly, one can move from the second extreme to the first by labeling or tagging more and more words with some tag. In various information extraction systems it is desirable to have the ability to control the tradeoff between high precision or high recall. In some scenarios a user may prefer that the system may label fewer words with a tag (low recall) yet to have the labeled words be tagged correctly (high precision), and in another scenarios the opposite is preferred, that is, labeling more words with some tag, yet at the price of low precision.

We propose the ability to perform such a system based on the confidence information outputted by various algorithms. We demonstrate the system using the task of named entity recognition. First, a NER algorithm produces a labeling for a given sentence, and then a confidence algorithm is used to output additional confidence score for each label. The system uses a tradeoff parameter $t \in [0, 1]$ to shift between the two extremes of high-recall and high-precision. The label of all words labeled with some tag, such as *Per* or *Loc* that their confidence is below the threshold t is replaced by the *N* label indicating that no tag is associated with that word. The larger the value of t is, the tag of more words that were labeled as named entities will be modified to a no-tag and the recall would be reduced. The lower the value of t is, the lower number of words for which their tag is modified, and the recall is higher. In the optimal case, with a perfect confidence estimation algorithm, only the tag of words labeled with incorrect tag would be changed, yielding higher precision with no decrease of recall. Fig. 15 illustrates such NER system. The words *Morgan Stanley* are first labeled as *Person* with low confidence score of 0.7, the word *Google* is labeled as *Organization* with high confidence score of 0.98 and the rest of the words are

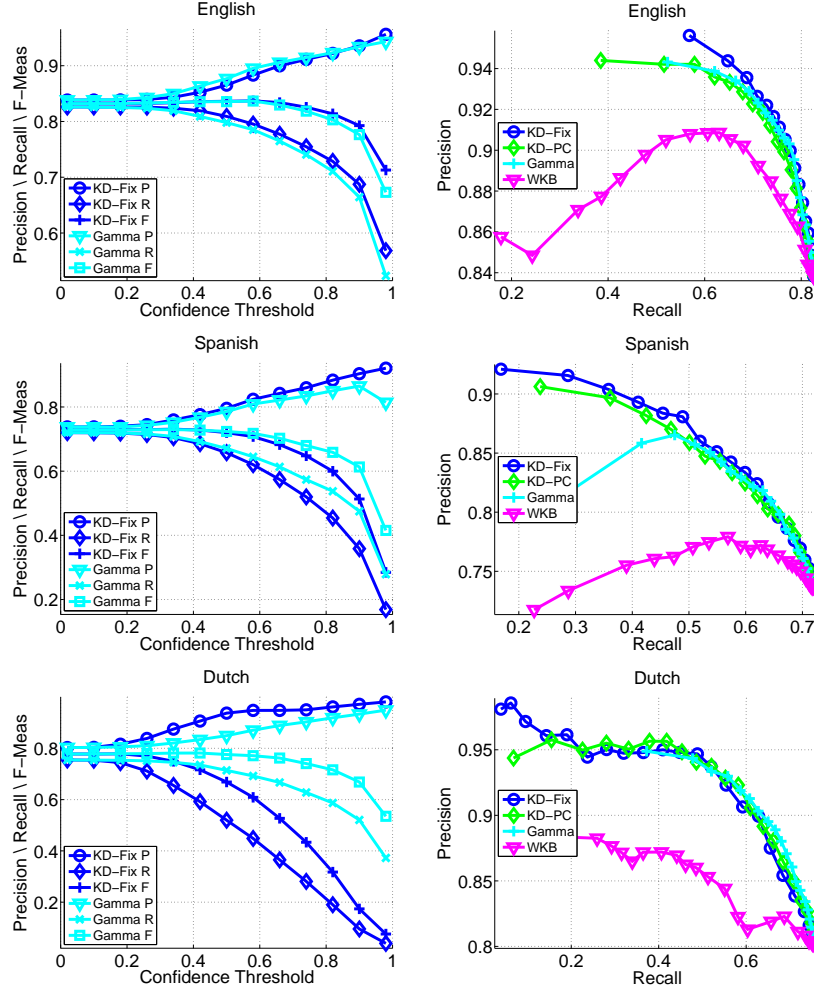


Figure 16: Trading recall for higher precision in NER. Left column present the precision, recall and f-measure as the confidence threshold is increased from 0 to 1 reflecting stronger bias for precision. The three lines of the same color are always (top to bottom) Precision, F-measure and Recall. Right column present precision-recall scores comparison for performing the tradeoff based on confidence scores provided by the different methods.

labeled with confidence score 1.0 as N indicating they are not part of named entity. In this example the tradeoff threshold t is set to 0.75, so the labels of *Morgan Stanley* that have confidence score below the threshold are replaced by N while the label of *Google* is not replaced as it has confidence score above the threshold. In this example, indeed *Morgan Stanley* was incorrectly labeled as *Person* instead of *Organization* so the replacement operation improves the

system’s precision.

The left column of Fig. 16 shows the NER precision, recall and f-measure as the confidence threshold value t increases from 0 to 1 which causes increasingly more tags such as *Per* to be replaced to a non-tag *N*. Each plot presents two sets of curves when using the confidence scores output by the **KD-Fix** algorithm and **Gamma** algorithm. The performance of **KD-PC** plot is similar to that of **KD-Fix** and of **WKB** is worse. Thus, both methods omitted for clarity. **Delta** is omitted since its output is not in the desired range of absolute confidence prediction. The top, middle and bottom curves for each of the two algorithms are precision, f-measure and recall respectively.

For English we observe a similar trend for both algorithms. For confidence threshold lower than ≈ 0.3 no labels are replaced and the precision and recall scores remains constant. For larger confidence threshold values the precision score increases as we expected, yet the recall score drops. This indicates that both correct and incorrect NE tags are being replaced with a non-tag *N*. For confidence threshold values between $\approx 0.3 - 0.7$ the f-measure score remains about constant while precision score increases from 0.83 to 0.90 and recall score drops from 0.82 to 0.77. This is a successful trade-off between recall and precision for the optimal f-measure value. For larger confidence threshold values $\approx 0.7 - 1$ the precision score continues to increase up to 0.95, yet at the price of significant drop in the recall score to 0.56 and the f-measure score drops as well.

For NER in Spanish, we observe that for confidence thresholds up to 0.6, both methods allow similar balanced precision recall tradeoff such that the f-measure score is steady. Yet, for threshold values greater than 0.6 the tradeoff based on **KD-Fix** confidence scores improves precision at cost of decreased recall more aggressively compared to tradeoff based on **Gamma**. The maximal precision score achieved using **KD-Fix** is 0.92 compared to only 0.87 with **Gamma**. In Spanish NER we also observe that when using **Gamma** for confidence, the precision score starts to drop along with recall scores for threshold values greater than 0.9. This indicates that more correct NE tags are replaced with a no-tag *N* compared with incorrect NE tags, which clearly is undesirable. A similar behavior of more aggressive tradeoff between precision and recall for **KD-Fix** than for **Gamma** is observed for Dutch. Here, the maximal precision score achieved using **KD-Fix** is 0.99 compared to only 0.95 with **Gamma**. Determining which behavior is preferable, aggressive or passive tradeoff, is application specific, yet for any given precision score having higher recall score is clearly preferable. For NP-chunking we observed similar trend (plots omitted) yet as precision starts from very high score of 0.95 the increase was less significant compared to the NER cases.

An alternative view of the same tradeoff is shown using the standard precision-recall curves in the plots in the right column of Fig. 16. Each of the plots shows the precision vs. recall for four confidence estimation methods algorithms: **KD-Fix**, **KD-PC**, **Gamma** and **WKB**, one plot for each dataset. The bottom-right point of each curve reflects the precision and recall before using our algorithms to filter or reduce tags. (In fact, all curves coincide at this point as the same

model is used to make label or tag the test data.)

As the confidence threshold value increases precision score improves and recall score decreases, yet each method goes via different route of trading-off precision and recall. An optimal confidence estimation method distinguishes between correct and incorrect NE tags labels, and thus improves precision while maintaining a constant recall values. Such optimal behavior is reflected by a vertical curve at the right area of the plots.

For all datasets WKB confidence score yields poor performance where the precision gain is small compared to the loss in recall. Furthermore, at some point precision drops as well. Additionally, KD-Fix and to some extent KD-PC allow the system to achieve higher-values of precision (curve ends with high value). Gamma achieves similar or slightly better precision values for high-recall, yet is not able to improve precision compared with KD-Fix (NER English and NER Dutch), or even the precision drops together with recall (NER Spanish).

We experimented also in performing tradeoff in the opposite direction: trading precision for higher recall. We used similar approach as described above. For words labeled with a no-tag N and with confidence score lower than some threshold t , we replaced the N with some tag, which had the second highest score value according to the prediction model. By construction, a tag of some NE (such as *Per*) will be chosen. This tradeoff task is harder than trading-off recall and precision as described above, as even if a word that is incorrectly labeled with a no-tag N is identified, still the algorithm is required to choose what tag should it be labeled with. We observed that our confidence estimation methods detect effectively incorrect no-tag labels N . Using KD-Fix method the average confidence score of all the words labeled incorrectly with a no-tag N is 0.6, 0.4 and 0.3 respectively in NER English, Spanish and Dutch. These values are low compared to the high average confidence scores of 0.99, 0.98 and 0.92 respectively, of all words assigned correctly with a no-tag N (Fig. 11 illustrates the low overlapping in the distribution of confidence scores between the correct and incorrect labels). Yet choosing the correct tag for a word is a hard task. Eventually recall values for all three languages improved at most by 0.02 while precision score dropped by ≈ 0.2 .

We therefore made the task easier by merging the four NE categories (*Person*, *Location*, *Organization*, *Misc*) to a single NE category. A word that is labeled with low confidence as no-tag N can now be tagged as NE without committing to a specific category. The results are presented in Fig. 17. We see that using a single NE category improves the base precision and recall scores in all three datasets, the f-measure scores for English, Spanish and Dutch improve from 0.83, 0.72, 0.77 to 0.94, 0.93, 0.94 respectively (these f-measure scores are close to the score achieved for NP chunking task which also has just a single tag category).

For English when using KD-Fix confidence scores to tradeoff we observe that for confidence threshold lower than ≈ 0.3 no labels are replaced. Then for confidence threshold values between $\approx 0.3 - 0.9$ the f-measure score remains about constant (even slightly improves) while recall score increases from 0.94 to 0.97 and precision score drops from 0.95 to 0.92. This is a balanced trade-off

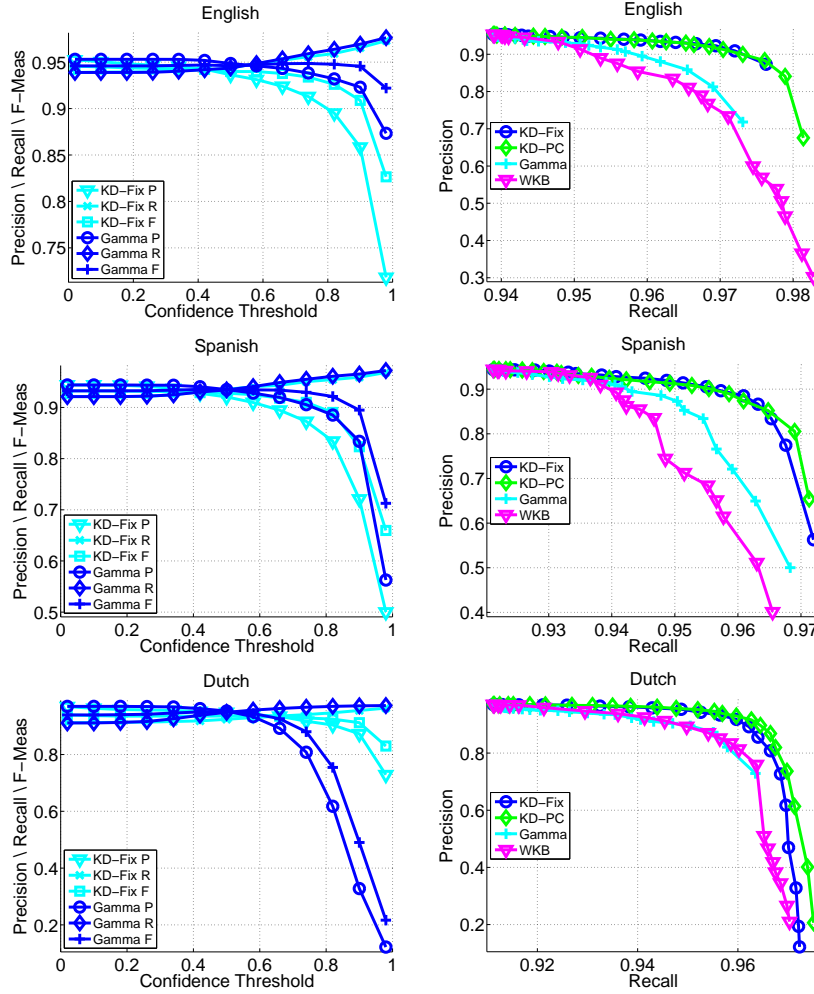


Figure 17: Trading precision for higher recall in NER. Left column present the precision, recall and f-measure as the confidence threshold is increased from 0 to 1 reflecting stronger bias for recall. Right column present precision-recall scores comparison for performing the tradeoff based on confidence scores provided by the different methods.

between recall and precision for the optimal f-measure value. For confidence threshold values greater than 0.9 the recall score increases a little more almost to 0.98 but the precision score drops to 0.87 and the f-measure score drops as well. Using **Gamma** confidence score for this dataset allows similar improvement in recall, but the precision scores drops significantly even for low confidence threshold values and falls to 0.72. Similar quantitative behavior was observed both for NER in Spanish and Dutch.

Dataset	Random	KD-Fix	Effort reduction
NER English	38K	25K	34%
NER Spanish	80K	60K	25%
NER Dutch	35K	23K	34%
NP chunking	62K	43K	30%

Table 12: Effort reduction in number of required word annotations when using active learning based on KD-Fix confidence scores compared to random sentence annotation.

The right column of Fig. 17 present the precision-recall curves using all the confidence estimation methods algorithms: KD-Fix, KD-PC, Gamma and WKB, one plot for each dataset. The top-left point of each curve reflects the precision and recall before labeling any low confidence no-tags words as NE. As the confidence threshold value increases recall score improves and precision score decreases.

For all datasets KD-Fix and KD-PC perform better than the other methods by maintaining higher precision score for the same recall scores, and in Spanish and Dutch datasets they also allow the system to achieve higher recall values. In English WKB allowed achieving the highest recall value yet at cost of very low precision.

Finally, we note that such an experiment is not relevant in the context of parsing, as each word is assigned to another word (with an edge), and the asymmetry in NER labels of having tags and no-tags does not exist.

8.2 Active Learning

In active learning, algorithms choose which example would be labeled and be included in the training set. The rational is that the algorithm would choose to label examples which their label contribute the most to the learning process. Other examples, often the easy ones, will not be chosen for labeling as they are not adding to the learning process.

In a typical active learning setting there exists a large set of unlabeled data and a small set of labeled data. Learning is performed in iterations. On each iteration the current set of labeled data used to build a model, which is then used to choose a subset of examples to be labeled from remaining unlabeled examples. Many active learning algorithms differ in the way this subset is chosen. We use the confidence estimation methods for this purpose.

The experimental protocol we used is as follows. The initial set of labeled examples contains 50 annotated sentences, and the initial set of unlabeled examples contains 9K sentences. Evaluation is performed using an additional test set of 3K sentences. Learning is performed using CW and then the resulting model and the confidence methods are applied to the set of remaining unlabeled sentences, yielding a rank over these sentences. Indeed, in standard binary or even multiclass prediction, many active learning algorithms are making a prediction

for each and every example that is not labeled yet. For sequence prediction problems, labeling sentences is time consuming. Thus, on each iteration the algorithm first selects random $1K$ sentences and a prediction (and confidence estimation) is performed only to this set. The algorithm then picks the 10 sentences with the least confident value, which are then annotated and accumulated to the set of labeled data examples. Every such 10 iterations (that is adding 100 sentences) the performance of the resulting model is evaluated using the evaluation set. The process is repeated until $5K$ sentences are labeled.

The experiments reported above were focused in estimating confidence for *individual words*. If for example, the output is given to a human, it is realistic to ask the human to verify the tagging of individual words as indeed most words are labeled correctly by the model. When moving to active learning, the situation changes. Now, all the words in a sentence are not labeled, thus if a human is required to label a single word, she may need to label adjacent words as well, having additional effort. We thus focused in active learning in the sentence level rather than the word level. We defined the confidence in a prediction of a sentence to be the minimal confidence score over words in that sentence. Then the algorithm is ranking *sentences* according to their confidence, breaking ties by favoring short sentences (assuming short sentences contains a larger fraction of informative words to be labeled than long sentences).

We evaluated scoring sentences using the confidence score of few methods, **KD-Fix**, **KD-PC**, **Delta** and **Gamma**⁴. As a baseline we used random sentences selection.

The averaged cumulative f-measure vs. number of words labeled is presented in Fig. 18 (as above **KD-PC** curves are close to **KD-Fix** curves and omitted for clarity). Left panels summarizes the results for a short horizon (small number of total-words). In two datasets random selection has the lowest performance, while **Gamma** is worse in Spanish. There is not clear winner among the other methods: **KD-Fix** is the best for NP-Chunking while **Gamma** is best for Dutch. The right panels show the results for more than $10k$ training words, in log scale. In this scale, random selection performs the worst in all cases, and then again all the other methods performs about the same, except NER English where **Gamma** achieves lower performance.

As the goal of active learning is reducing the annotation effort, we compare the number of words required to be annotated when applying the proposed selection method using **KD-Fix** in order to achieve the same performance level as by random picking of $5K$ sentences. The results are summarized in Table 12 For NER English dataset only $25K$ words are required to achieve the same level of performance obtained by training on $38K$ random words - a 34% effort reduction. Similarly for Spanish, Dutch and Chunking about $12 - 20K$ words have to be annotated to achieve the same performance of random labeling, a 25 - 34% effort reduction.

⁴We (Mejer and Crammer, 2010) used two additional methods before, yet their performance was lower or about the same, and thus we omit them here for clarity.

9 Related Work

Confidence estimation methods for structured predication in NLP were investigated in previously and applied to tasks such as POS tagging, information extraction, machine translation, and automatic speech recognition (ASR).

Culotta and McCallum (2004) propose several methods for confidence estimation for single and multi-word fields, and for entire records in a CRF based information extraction system. They describe a constrained forward-backwards algorithm that defines confidence as the ratio of total probability of any labeling for a given sentence with the total probability given a labeling constraint which is taken as the extracted field. The constrained forward-backwards yields same confidence scores as **Gamma** a for single token yet when extended to multi-word field it performed better. Additionally, they used an external maximum entropy classifier to classify fields as correct or incorrect based of set of features describing the extracted fields. The resulting posterior probability of the "correct" label is used as the confidence measure. This method performed equally to the constrained forward-backwards method. Kristjansson et al. (2004) shows how to improve interactive information extraction system accuracy by high-lighting low confidence fields, computed using these confidence scores, for the user to inspect and correct.

Scheffer, Decomain, and Wrobel (2001) estimate confidence of single token label in HMM based information extraction system by a method similar to the **Delta** method we use. The label confidence score is the difference in the marginal probabilities of the best and second best label to the token. They use the single token confidence score to rank the labels and use this ranking for active learning.

Ma, Randolph, and Drish (2001) describe HMM based ASR system where word marginal score and difference in scores between the two best alternatives are used to compute per-word confidence measures, similar to **Gamma** and **Delta** methods we use. They train SVM based on these features for deciding which word candidates to reject.

Ueffing and Ney (2007) propose several methods for word level confidence estimation for the task of machine translation based on K-best translations. These methods are similar to the weighted and non-weighted K-best methods (KB and WKB) we use. They show the utility of the confidence scores for detecting incorrect translated words and for re-scoring candidate translations among the K-best alternatives and show improvement in translation quality.

Gandrabor, Foster, and Guy (2006) describe using a neural network as a dedicated confidence estimation layer and evaluate it for ASR and for machine translation tasks. Both the ASR and translation systems provide a probabilistic score to their outputs, yet the dedicated confidence estimation layer can combine features and account for addition information that is not available to the prediction system and thus provide more useful confidence scores. They show the advantage of using a dedicated layer in ASR for the single word level and in the concept-level (semantic phrases) by rejecting incorrect recognitions. In context of interactive machine translation system with sequences of 1-4 words

they gain advantage by avoiding incorrect translation suggestions.

About a decade ago, Argamon-Engelson and Dagan (1999) used committee voting to evaluate the uncertainty in an example in a HMM based POS tagger. The committee of HMM taggers are sampled from the trained model in a manner similar to KD-PC method we use. Each HMM parameter is independently sampled from normal distribution with mean value equal to the trained parameter value and with per-parameter standard deviation according to the number of examples the parameter value was estimated by and multiplied by a "temperature" coefficient. The committee of taggers were then used to produce a set of POS predictions and the uncertainty in each label is computed according to the disagreement among the committee predictions regarding that label. They used the uncertainty measure for guiding sample selection (active learning) and show that indeed this method reduces the required labeling effort compared to random or entire corpus labeling. However they did not evaluate directly the relative or absolute per-label confidence score for purpose such as detecting incorrect labels.

Confidence estimation was used in various additional setting of NLP applications such as binary and multi-class classification. For example, Delany et al. (2005) describe confidence estimation method in an email spam filtering system based on combination of k-Nearest Neighbors features such as agreement among the neighbors and distance to closest same and opposite prediction. Platt (1998) describes how to fit a sigmoid function to compute class posterior probabilities, that can serve as confidence scores, from the non-calibrated output score provided by the SVM in text classification tasks. Xu et al. (2002) use confidence estimation in a question answering system by mixture of few heuristic correctness indicators and show that these confidence scores are useful for selecting between alternative answer sources. Bennett, Dumais, and Horvitz (2002) use confidence scores, referred to as reliability-indicators, for combining predictions of different types of document classifiers. They show that confidence scores allows better aggregation of the prediction votes compared to other alternatives.

Finally, there has been much work on active learning for NLP applications including structured prediction tasks. For example Thompson, Califf, and Mooney (1999) use minimal confidence in the extraction rules of a rules-based information extraction system to select instances for annotation. Shen et al. (2004) use minimal margin of SVM along with considerations of instances representativeness and diversity in a NER system, and Baldrige and Osborne (2004) (see also (Osborne and Baldrige, 2004)) apply active learning for parsers.

10 Summary and Conclusions

We have studied few methods to estimate the *per-word* confidence in structured predictions. These algorithms were evaluated both in a relative settings and in a absolute setting. We also used the confidence score of these methods in two applications: increasing precisions while decreasing recall, and active learning. All-in-all we found that the two methods using sampling alternative models

KD-PC and KD-Fix yield the best results. The former is induced from the CW algorithms, while the later can be used with any linear model. Generally KD-Fix performed a little better except for sequential labeling in absolute setting where KD-PC was better.

These methods were also found useful in increasing precision vs recall in sequence labeling tasks. Additionally, we showed that when combining these methods with active learning, one can reduce annotating effort by at least 25% compared to random sampling. Understanding the theoretical properties of the problem and our algorithms remains an open problem to be addressed in the future.

acknowledgments

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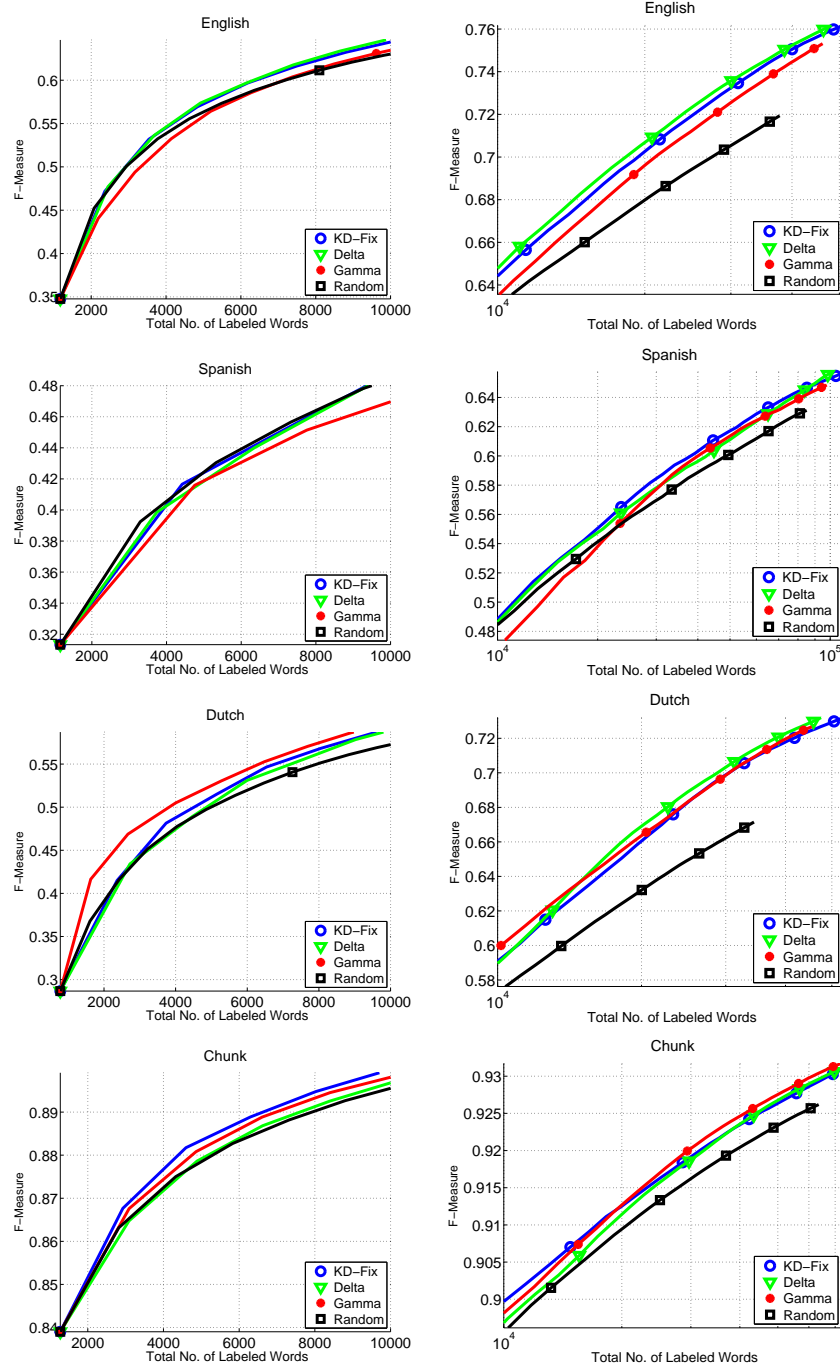


Figure 18: Averaged cumulative F-score vs. total number of words labeled. The left panels show the results for the first 10,000 labeled words, the right panels show the results for more than 10k labeled words.

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